The Multiple Inflection Generator: A generalized connectionist model for cross-linguistic morphological development.

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Introduction

Computational models and theories of morphological development

Computational models have advanced our understanding of the mechanisms that underlie language acquisition. A particular class of computational models, referred to as artificial neural network or connectionist models, are especially well suited to the study of development. These models offer an intuitive framework in which empirical phenomena in language acquisition are explained in terms of interactions between a language-learning system that incorporates general properties of computations in the brain and statistical properties of the linguistic environment to which it has been exposed. In the domain of inflectional morphology, an extensive literature of connectionist models has offered mechanistic explanations for the emergence of a wide range of empirical phenomena, including accuracy rates and error patterns in regular and irregular inflection, type and token frequency effects, and preferences for the inflection of novel items (e.g. Joanisse, 2004; Mirković, Seidenberg, & Joanisse, 2011; Plunkett & Juola, 1999; Plunkett & Marchman, 1991, 1993, 1996; Rumelhart & McClelland, 1986; Thomas, 2005; Thomas, Forrester, & Ronald, 2013; Thomas & Karmiloff-Smith, 2003; Thomas & Knowland, 2014; Westermann & Ruh, 2012; Woollams, Joanisse, & Patterson, 2009).

A key feature of connectionist models of language acquisition is that the language-learning systems they presuppose do not bear prior linguistic knowledge in terms of, for example, an explicitly defined past-tense formation rule. Instead, they are constrained by low-level input and output (target) representations of a linguistic environment that they are assigned, and their power to learn associations between these forms. Connectionist models of language acquisition demonstrate the gradual emergence of linguistic behavior during the progression of a learning process, in which a connectionist learning system extracts statistical regularities encoded probabilistically and in low-level (‘sub-symbolic’) features of the language environment it has been exposed to. In connectionist models of Inflectional Morphology, the emergent linguistic behavior may refer to both inflectional rules and exceptions. This implies a key property of connectionist accounts of language development, that regular and irregular inflections are accommodated within a single processing mechanism (‘single-route’).

An alternative perspective on morphological development is given by the so-called dual-route (Marcus et al., 1992; Pinker, 1984, 1991, 1995, 1999) accounts of language development. These accounts differ from connectionist models in two important ways. Firstly, and akin to linguistic theories (Chomsky, 1965, 1986, 1998; Pinker, 1994), they presuppose innately specified linguistic knowledge, in the form of linguistic rules operating on symbols (e.g., a verb stem or a suffix). Secondly, dual-route accounts suggest that two separate systems are involved in morphological development. A rule-based system supports the consistent application of rule operations on all symbols corresponding to regular verbs, while a rote-memory system is an associative mechanism supporting the retrieval of irregular verbs. Aspects of children's performance in the learning of regular and irregular inflection are explained on the basis of the different computational properties of these two systems (Pinker & Ullman, 2002).

Connectionist and dual-route accounts of inflectional morphology have presented important theoretical progress as they competed to address psycholinguistic data on the acquisition of inflections. The two approaches have emphasized on different levels of description, connectionist models demonstrating principles of associative learning and the dual-route accounts relying upon rule-based learning. Despite their differences, connectionist and dual-route theories approaches have also presented similarities. For example, both approaches have supposed a bipartite structure for the learning of regular and irregular inflection, although they differed with respect to whether this division corresponds the weighting of different types of information or 'cues' (phonology vs. semantics; Joanisse & Seidenberg, 1999) or different types of mechanisms (dual-route model).

A relative strength of connectionist approaches over dual-route accounts of language acquisition is implementation. Connectionist approaches to language development have been established and specified by putting their main tenets and assumptions into practice (see also Seidenberg & Joanisse, 2003). By contrast, the detailed developmental behavior that would follow from the processing assumptions of the dual-route model remains unknown, imposing limits on its testability, or indeed its adequacy to explain the empirical data.

Generality

Connectionist and dual-route accounts of morphological development have often focused on the English past tense, under the assumption that this quasi-regular subdomain taps the main cognitive processes involved in the acquisition and use of morphological knowledge. An important challenge, however, for theories and models of morphological development is to demonstrate their generality: across inflectional paradigms, across grammatical classes, and across languages.

It is important to address the acquisition of multiple inflectional paradigms, as the presence of a specific cognitive system dedicated to the processing of a particular inflection/class – e.g., past tense and not, say, progressive or plural – is unlikely (cf. Plunkett & Juola, 1999, also evidence from neuroimaging: Tyler, Bright, Fletcher, & Stamatakis, 2004; Vigliocco, Vinson, Druks, & Cappa, 2011; Yokoyama et al., 2006). Further, the acquisition of multiple inflectional paradigms within the same system gives rise to numerous interactions. Empirical data are available to constrain how such interactions manifest in first language acquisition. For example, English inflectional morphemes emerge in a consistent order in child language (Brown, 1973; de Villiers & de Villiers, 1973, 1986). Another example, commission errors, i.e., applying a progressive suffix in the past tense, are rare (cf. past-tense data in van der Lely and Ullman, 2001). To address such data, models and theories of morphological development need to examine the acquisition of fully-fledged inflectional systems, rather than piece-meal accounts for the learning of individual inflections.

It is also important to consider cross-linguistic variation. English has a simple morphological system, characterized by predominant regularity. This is not the case in many other languages, such as Arabic (Forrester & Plunkett, 1994; Plunkett & Nakisa, 1997), French (Prevost, 2009), German (Nakisa & Hahn, 1996), Icelandic (Ragnarsdottir, Simonsen, & Plunkett, 1999), Modern Greek (Stephany, 1997), or Serbian (Mirković et al., 2011). Models and theories should work across language typologies and should have no language-specific structures (cf. Hutzler, Ziegler, Perry, Wimmer, & Zorzi, 2004; Seidenberg, 2011 on reading development models). The language generality of a model's architecture cannot be tested unless it is applied to acquiring the IM of another language.

The Multiple Inflection Generator (MIG)

In this paper, we present a connectionist model for the acquisition of inflectional morphology implementing a scaled-up inflectional system, which comprises three grammatical classes (nouns, adjectives, and verbs) and multiple inflections within a grammatical class (e.g., English verbs: base forms, past tense, progressive, third person singular; English nouns: base forms, plural, genitive). At the same time, the model has a cross-linguistic dimension. It uses a common set of modelling and theoretical assumptions to address empirical phenomena in morphological development in two languages with different degrees of morphological richness, namely English and Modern Greek. Elsewhere, we show how the model is also general across typical and atypical development (Karaminis, 2012; Karaminis & Thomas, in preparation).

The Multiple Inflection Generator (MIG) combines features of previous connectionist models that showed the potential of the connectionist framework to address the acquisition of multiple inflections either within (multiple verb inflections: Hoeffner, 1992; Hoeffner & McClelland, 1993; MacWhinney & Leinbach, 1991; multiple noun inflections; Mirković et al., 2011) or across grammatical classes (verb past tense/ noun plural: Plunkett & Juola, 1999). The MIG synthesizes and scales-up these approaches, including multiple inflections within *and* across grammatical classes. The model is therefore novel in addressing developmental data for the acquisition of fully-blown inflectional systems, for example the order of emergence of English inflectional morphemes in child language (e.g., Brown, 1973). These data are accounted for whilst also capturing fine-grained developmental data within individual inflections (e.g., developmental error patterns of the past tense and the rates in which these occur). The MIG addresses the serious challenge to demonstrate its robustness to interactions arising from the acquisition of multiple inflections of multiple grammatical categories within the same processing system.

Another source of inspiration for the MIG was models showing that the connectionist framework can account for the acquisition of morphology in non-

English languages (e.g., Arabic Plural: Forrester & Plunkett, 1994; Serbian noun inflections: Mirković et al., 2011; German plural: Nakisa & Hahn, 1996; Plunkett & Nakisa, 1997; German past tense: Ruh & Westermann, 2009). The MIG extends this earlier modelling work in two ways. Firstly, it addresses the acquisition of scaled-up inflectional systems (multiple grammatical classes *and* multiple inflections within a class) in non-English languages. Secondly, it applies the same cognitive architecture to the acquisition of different morphological systems. This sense of cross-linguistic generality has not been addressed in earlier connectionist models of non-English morphology. For example, models of the acquisition of the so-called minority-default systems (e.g., German plural) have addressed empirical data showing that certain rare conjugational rules were preferred to more frequent rules for the inflection of non-words. These models employed cognitive architectures that learnt to categorize phonological forms to conjugational classes rather than architectures learning mappings between phonological forms of stems and inflected words, as in models of English morphology.

The MIG is novel in assuming that the same architecture underlies the acquisition of morphology in different languages. The broader theoretical position on which the model was based is that the acquisition of inflectional morphology involves learning to integrate multiple types of information (‘cues’: stem phonology, lexical semantics, grammatical class, and target inflection information) so as to produce appropriately inflected phonological word forms, in accordance with the grammatical context. The MIG is novel in instantiating a multiple-cue architecture in two different language; in demonstrating how this common initial processing structure changes when exposed to different linguistic environments; and in demonstrating how these changes relate to the emergence of cross-linguistic patterns in morphology.

A key step in our research design was the development of two training sets representing the linguistic environment of a child acquiring English and Modern Greek as a first language. These reflected key characteristics of the system of IM in English and Modern Greek, as well as key cross-linguistic differences with respect to IM and phonology. The two training sets were used to train the same neural network architecture, with minor modifications only to accommodate cross-linguistic differences in phonology. English was modeled as a language making wide use of morphologically unmarked forms and employing a simple morphological system characterized by predominant regularity. Modern Greek, on the other hand, was modeled as a language featuring obligatory morphological marking for nouns, adjectives, and verbs, and a rich system of inflectional morphology that included numerous conjugational classes (Stephany, 1997). An important part of the model was a frequency structure that reflected frequencies of grammatical classes, inflection types, regular and irregular paradigms, and conjugational classes within each language (type frequencies). This structure was largely based on measurements of text corpora (English: Francis & Kučera, 1982; Modern Greek: Hatzigeorgiu et al., 2000), and was combined with a simplified two-level frequency scheme for individual exemplars (token frequency; high vs. low).

We show that a simple feed-forward architecture receiving multiple cues as input and trained to produce phonological forms corresponding to appropriately inflected words in the output layer is able to learn training sets representing fully-blown morphological systems, either similar to English or to Modern Greek. We also show that this multiple-cue architecture acquires English and Modern Greek morphology in a psycholinguistically plausible manner. We analyze results from simulations with the MIG to delineate how a large body of empirical effects in the acquisition of English and Modern Greek IM emerges through interactions between general properties of a PDP learning system (e.g., similarity-based processing of distributed activation patterns) and statistical characteristics of the corresponding training sets, such as frequencies of different inflections and individual exemplars, the level of complexity of different inflections (e.g., progressive simpler than past tense), and similarities and differences between different types of mappings. Finally, we study the emergent functional structure that allows for the flexible integration of different cues within and across languages, and discuss similarities and differences with the dual route (Pinker, 1991, 1994, 1999) and optional infinitive (Wexler, 1994, 1999) theories.

Background

Cross-linguistic differences of English and Modern Greek with respect to IM

The principal research aim of the MIG was to apply the same multiple-cues connectionist architecture to two languages very different in character with respect to inflectional morphology. The main cross-linguistic differences between English and Modern Greek with respect to morphology that the model focused on were as follows:

1. English employs morphological marking for fewer grammatical categories than Modern Greek.

The English system of inflectional morphology is summarized in Table 1. English presents a high and typologically rare degree of morphological simplicity (Ragnarsdottir et al., 1999, p.578) and uses morphological suffixes to mark eight grammatical categories, namely the plural and the possessive of nouns, the progressive and the third person singular of the present tense of verbs (henceforth: 3rd singular), the past tense of verbs and the past participle of verbs, and the comparative and superlative of adjectives. By contrast, Modern Greek is a highly inflecting language that inflects most grammatical classes (six out of ten), namely articles, nouns, adjectives, pronouns, verbs, and participles (Holton, Mackridge, & Philippaki-Warburton, 2003; Triandafillidis, 1941). Nouns, adjectives, articles, pronouns, and participles follow nominal inflection and present inflected forms (or types) corresponding to different cases (nominative, genitive, accusative, vocative) of the singular and the plural number (Triandafillidis, 1941, p.210). Verbs present types corresponding to different persons of the singular and the plural number and these types also bear morphemes marking tense, aspect, mood, and voice (Stephany, 1997, p.185). A simplified version of verb morphology in Greek is presented in Table 2.

2. English makes extensive use of unmarked (root) forms, whereas Modern Greek completely lacks them.

Many grammatical categories are not marked in English. For example, nouns do not have grammatical gender, while verbs are marked for person only in the 3rd singular. Unmarked forms of nouns, verbs, and adjectives are therefore used extensively, in all cases where a morphological suffixation rule does not apply. On the other hand, there are no root forms of nouns, adjectives, and verbs in Modern Greek (Stephany, 1997; Varlokosta, Vainikka, & Rohrbacher, 1996). Word stems are bound morphemes, i.e., they cannot stand alone as individual words, and always need to be combined with suffixes to express case (for nominal inflection), person (for verbal inflection), and number (for nominal and verbal inflections).

3. English marks words for a single grammatical category (at most), whereas Modern Greek fuses multiple inflectional morphemes in the same word forms.

As shown in Table 1, the English system of inflectional morphology is based on morphological suffixes. On the contrary, the system of inflectional morphology in Modern Greek is synthetic and fusional (Joseph, 2008, p.486). Case, person, and number are realized by fusing the stem, i.e., the part of the word that remains the same across the different types, with suffixes (Triandafillidis, 1941, p.210). Other grammatical categories may require the use of prefixes, infixes, as well as phonologically predicted modifications of the stem and stress shift (e.g., perfective past tense of verbs; Stavrakaki & Clahsen, 2009).

4. English morphology is either fully regular or based on a dichotomy between regulars and irregulars, whereas Modern Greek morphology is based on multiple conjugational categories.

In English, inflections are either fully-regular or they can be described in terms of a clear-cut dichotomy between a predominant class of regulars and a minor class of irregular examples (e.g., past tense: 160 regulars vs. 10,000 regulars; Marslen-Wilson & Tyler, 1998). This is despite the fact that regular inflections may consider allomorphic subcategories, and irregular inflections may consider quasi-regular clusters (e.g., irregular past tense; identity: *set/set*, vowel-change: *know/knew*, arbitrary: *be/was*). By contrast, there are multiple conjugational classes for both nominal and verbal inflections in Modern Greek (Holton et al., 2003; Stephany, 1997; Triandafillidis, 1941, Varlokosta et al., 1996). An additional source of complexity is the combination of conjugational categories corresponding to individual grammatical features. For example, verb forms are realized fusing stems corresponding to the perfective or the imperfective aspect, with suffixes for person and number, and possibly an infix for marking the past tense (e.g., Holton et al., 2003, p.108-119). As alternatives exist for all these procedures, the result is an especially complex system of verb conjugation (Stephany, 1997, p.185).

Target empirical phenomena for the acquisition of English inflectional morphology

The acquisition of English IM has been studied extensively in the literature and the available empirical data are ample. Table 3 summarizes the five key phenomena that have been observed in these data and were set as the target empirical phenomena for the MIG. Asterisks in the second column mark phenomena within English that, to our knowledge, have not been addressed previously with computational modeling. The third column includes the studies that provided data we used for comparisons with the MIG, and the last column provides a preview on how successful the model was in simulating these data (quantitative fit, qualitative fit, or dissimilar to the data; see Method and Results for details).

Target empirical phenomenon ENG1: Order of emergence of inflections

Target empirical phenomenon ENG1 refers to the order in which different inflections emerge in child language. The relevant data come from the longitudinal corpus-based study of Brown (1973) and the cross-sectional study of de Villiers and de Villiers (1973). Brown (1973) analyzed utterances produced by three children to compare the stages at which the rates of correct usage of different grammatical morphemes in obligatory contexts exceeded 90% for the first time (Brown's criterion for acquisition; Brown, 1973). The progressive of verbs was acquired first, followed by the plural of nouns, the irregular past tense of verbs, and the possessive of nouns. Regular past tense and 3rd person singular were acquired later in development. De Villiers and de Villiers (1973) obtained a similar order under a cross-sectional research design.

In both Brown (1973) and de Villiers and de Villiers (1973), the order of emergence of inflections was highly correlated (rank-order correlations >0.8) with the complexity of individual inflections. The level of complexity of different inflections was the number of rules required for the derivation of morphemes according to the transformational grammar of Jacobs and Rosenbaum (1968) (cumulative syntactic complexity, cf. Brown, 1973) or the number of unitary meanings that morphemes encode in child language (cumulative semantic complexity, cf. Brown, 1973). There were, however, no reliable correlations, between morpheme frequencies in parental speech and the order of acquisition (de Villiers and de Villiers, 1973).

The aim of the MIG with regards to target empirical phenomenon ENG1 was to generate a rank order for the range of English inflections studied in Brown (1973) and de Villiers and de Villiers (1973). The order of emergence of inflections was based on the same criterion for acquisition (90% accuracy; Brown, 1973) and was compared to the empirical data numerically, i.e., based on the calculation of correlation coefficient values between vectors of rank orders in the model and the data. We also examined how the complexity of different inflections, as well as type frequencies derived from the tagged Brown Corpus (Francis & Kučera, 1982) and embedded in the training set and the training regime of the model related to the order of acquisition.

Target empirical phenomena ENG2, ENG3, ENG4, and ENG5: Accuracy, error patterns, frequency effects, and generalization in quasi-regular domains

Target empirical phenomena ENG2 to ENG5 refer to developmental patterns across a range of empirical findings, such as differences in the accuracy rates in regular and irregular inflection, the occurrence and rates of particular error types (omission errors: *Yesterday, I eat a candy*; overgeneralizations: *Yesterday, I eated a candy*; and blend errors: *Yesterday, I ated a candy*), the presence of increased effects of token frequency in irregular inflection compared to regular, and the high rates of rule-based inflection of novel items. The data used to assess the ability of the MIG to simulate target empirical phenomena ENG2 to ENG5 come from a past tense elicitation task considered in van der Lely and Ullman (2001). We performed qualitative and quantitative comparisons between the developmental trajectories of the MIG and three groups of typically developing children of increasing mean age (three groups of 12 children, with a mean age of 5;9, 6;11, and 7;11 years) in that study. The comparison focused on periods of the training time of the model in which the performance of the MIG matched the empirical data from the three groups of children on accuracy rates in the regular past tense.

We also considered evidence from other studies on complementary qualitative characteristics of target empirical phenomena ENG2 to ENG5. This evidence referred to the observation that the rates of blend errors are lower than the rates of overgeneralization (Marcus et al., 1992), the rates of rule-based inflection of novel items increase with their phonological similarity to existing regulars (Prasada & Pinker; 1993), and the rates of overgeneralization are higher in the plural number than the past tense (e.g., English plural: Marchman, Plunkett, & Goodman, 1997).

The main research aim of the MIG with regards to target empirical phenomena ENG2 and ENG5 was to examine whether qualitative and quantitative characteristics of developmental patterns in accuracy rates, frequency effects, error patterns, and the inflection of novel items can be simulated in a neural network architecture exposed to inflectional mappings corresponding to a fully-fledged English morphological system. This issue has not been addressed under the connectionist framework and is not trivial. For example, the empirical data (e.g., van der Lely & Ullman, 2001) suggest that children do not make commission errors, i.e., they do not apply suffixes corresponding to the progressive of verbs (-ing) or the 3rd singular/noun genitive/noun plural (-s) in cases where a verb stem needs to be marked for past tense. To acquire English in a psycholinguistically plausible manner, the MIG should also not produce this error type. In a system performing similarity-based processing and exposed to a training set in which words are frequently marked with an -s suffix, such responses might well occur.

Three further phenomena were beyond the scope of the current version of the MIG for reasons of simplicity and tractability. The three limitations of the model were the following: 1) it did not address data on the U-shaped learning curve for irregulars, as empirical effects characterizing the very early morphological development were beyond its scope; 2) it did not study conditions under which novel stems rhyming with existing irregular stems are inflected irregularly, i.e., similarly to their rhymes; 3) it did not address data focusing on phonological consistency, e.g., semi-regular clusters within irregular inflection, e.g., vowel-change (know/knew, grow/grew).

Target empirical phenomena for Modern Greek

The target empirical phenomena for the acquisition of Modern Greek IM are listed in Table 4. Target empirical phenomena GR1 to GR4 refer to noun morphology; target empirical phenomena GR5 to GR7 refer to adjective morphology; and target empirical phenomena GR8 to GR10 refer to verb morphology. Similarly to Table 3 (target empirical phenomena for English), Table 4 includes information on the studies that provided the empirical data for comparison (third column); whether it was possible consider quantitative comparisons between the simulation output and the data (fourth column); and a preview of the model's successes and failures in capturing the different phenomena.

Target empirical phenomena GR1 to GR9 were addressed based on qualitative descriptions of the course of acquisition of Modern Greek, mainly from corpus-based approaches (Stephany, 1997; Stephany & Christodou, 2009; and Varlokosta et al., 1996). Quantitative comparisons were possible for target empirical phenomenon GR10. The data of Stavrakaki and Clahsen (2009) on the acquisition of the perfective past tense defined developmental trajectories for accuracy rates and error patterns in different conjugational classes. These data were used to perform comparisons parallel to those between the MIG and the data of van der Lely and Ullman (2001) on the acquisition of the English past tense.

As discussed earlier, the MIG targeted important cross-linguistic differences between English and Modern Greek with respect to morphology (Modern Greek marking more categories, lacking unmarked forms, fusing the stem with multiple morphemes, and presenting multiple conjugational classes). To help the reader who is not familiar with Modern Greek establish a certain level of correspondence between the key target empirical phenomena in the acquisition of English and Modern Greek IM, we group the latter into four main types: 1) phenomena related to an analogue of the Optional Infinitive stage (Wexler, 1994) in Modern Greek; 2) phenomena related to the order of emergence of different grammatical features; 3) phenomena related to the developmental profile of the perfective past tense based on the sigmatic/non-sigmatic distinction; and 4) phenomena related to the effects of phonological salience in the perfective past tense.

Target empirical phenomena related to analogues of the Optional Infinitive stage: GR1, GR5, GR8

The absence of unmarked forms in Modern Greek implies that inflection omission errors are not possible. This is problematic for accounts of morphological development such as the Optional Infinitive (Wexler, 1994; see also Rice, Wexler, & Cleave, 1995) positing that this error type is due to certain grammatical categories (e.g., Tense and Agreement; Schütze & Wexler; 1996) missing, being underspecified, or optional in early child language. Indeed, later versions of this theory (e.g., Unique Checking Constraint, UCC; Wexler, 1999) have included modifications to address phenomena in acquisition of other languages (e.g., Danish; Wexler, 2000). In a similar vein, a number of studies on the acquisition of IM in Modern Greek aimed to identify early developmental error patterns that could be an analogue of omission errors in the productions of children acquiring English as a first language.

With regards to verbal morphology, target empirical phenomenon GR1 refers to the observation that early productions of children are characterized by the overuse of verb forms bearing the perfective or the imperfective stem and ending in -i (i-forms, Katis, 1984; Stephany, 1997; Varlokosta et al., 1996). This could correspond to a developmental stage descriptively similar to the Optional Infinitive stage with these forms serving as the default paradigm (unmarked). Katis (1984) and Stephany (1997) proposed that the overuse of i-forms denotes that 3rd person singular forms (see Table 2, present tense), which are acquired earlier than other person/numbers, are overgeneralized in inappropriate contexts. Therefore, the overuse of i-forms corresponds to Subject-Verb agreement errors, in the sense that children fail to mark verbs in the person denoted by the subject of the sentence. Under an alternative account, i-forms correspond to the active perfect participle, a verb form without person and tense marking (Varlokosta et al., 1996).

With regards to noun inflection, target empirical phenomenon GR5 describes the overuse of noun forms ending in a vowel, which according to Stephany (1997, p.213) correspond to adult accusative singular forms of the three genders, as well as the nominative of neuter and feminine nouns. Such forms have been termed as base forms or all-purpose unmarked forms (Stephany & Christofidou, 2009) of nouns. Adjective inflection is similar to noun inflection apart from the fact that adjectives are also inflected with respect to gender (while nouns can be one of the following: masculine, feminine or neuter). Target empirical phenomenon GR8 refers to the overuse of neuter forms of adjectives, and in particular, nominative/ accusative forms of singular number, in other contexts (Stephany, 1997, p.224).

The aim of the MIG with regards to the target empirical phenomena GR1, GR5 and GR8, was to capture early developmental error patterns in the inflection of nouns, verbs, and adjectives. Unlike the English version of the model, these phenomena were addressed in the absence of a strong prototype effect of base-form-to-base-form mappings in the training set. This was a challenge of the model as it implied different types of error patterns for nominal and verbal inflection.

Target empirical phenomena related to the order of emergence of grammatical features: GR2, GR3, GR4, GR6, GR7, and GR9

Target empirical phenomena GR2, GR3, GR4, GR6, GR7, and GR9 refer to the order of emergence of the different grammatical features that the language distinguishes. For example, target empirical phenomenon GR2 states that the number of nouns emerges earlier than case in child language (Stephany, 1997). Since nouns in Modern Greek bear obligatory marking of case and number (no unmarked forms), identifying the order of acquisition of different grammatical features is based on their contrastive use (Stephany, 1997). Thus, as early forms of nouns correspond to accusative singular forms, the acquisition of case is denoted by the emergence of genitive singular, while the acquisition of number is denoted by the emergence of accusative forms of the plural number.

The MIG generated data on the order of emergence of different grammatical features in Modern Greek by adopting Brown's (1973) criterion for the acquisition of inflections, extended from the English model. Findings from the simulation were compared qualitatively with the descriptions in the empirical data.

Target empirical phenomenon related to developmental error patterns: GR10

Target empirical phenomenon GR10 refers to the detailed developmental profile of the acquisition of the perfective past tense in Stavrakaki and Clahsen (2009). These authors considered the fundamental distinction between a statistically dominant class of verbs that form their past tenses based on morphological modifications according to the so-called sigmatic rule (conjugational classes 1 and 3, in Table 2) and a less frequent class of verbs having non-sigmatic past-tense forms (conjugational classes 2a and 2b, in Table 2). They found that children's scores in an elicited production task were higher in the sigmatic (regular) than in the non-sigmatic (irregular) category and this difference was more pronounced at earlier developmental stages. Children overapplied the sigmatic rule in the non-sigmatic category but not vice versa. In the category of sigmatic verbs, incorrect responses were imperfective past-tense forms or perfective past tense forms of other verbs. Finally, sigmatic past-tense forms were preferred for novel rhymes of both existing sigmatic and existing non-sigmatic verbs.

The MIG aimed to simulate the learning profile of the perfective past tense in Modern Greek considering quantitative comparisons with the human data, i.e., on the calculation of a correlation coefficient value for the corresponding vectors. The model and the human data were matched on performance on the sigmatic (‘regular’) category, in parallel with the comparison with English past-tense data of van der Lely and Ullman (2001). Similar comparisons between the model and the human data were performed regarding the inflection of novel items.

Method

General assumptions and simplifications

Our research design entailed the development of a basic neural-network architecture and a training procedure using training sets that reflected the main properties of the systems of inflectional morphology in English and Modern Greek. Only minor adjustments were considered for the basic architecture in the two versions of the model, accommodating cross-linguistic differences with respect to phonology.

The overarching design principles of the MIG were as follows: 1) there is an inflection system that produces inflected forms of words appropriate to the grammatical sentence context; 2) this system is responsible for producing all inflection types; 3) multiple information sources are available to drive the output of the system and therefore cues to predict the form of a given output may be exploited flexibly across development depending on the demands of particular inflection paradigms; and 4) empirical patterns in the acquisition of different languages reflect properties of the linguistic environment to which the child is exposed.

We assumed that the mechanism for inflectional morphology is embedded in a larger set of systems, which provide the MIG with the different types of information (see Hoeffner & McClelland, 1993). A perceptual system makes phonological representations available (e.g., Plunkett & Marchman, 1991, 1993, 1996), while a lexical knowledge system provides representations of lexical semantics (e.g., Joanisse & Seidenberg, 1999). A grammatical knowledge system contributes representations of grammatical classes (e.g., Plunkett & Juola, 1999). And a syntactic processing system signals the morphological modifications required by the context of the sentence (e.g., MacWhinney & Leinbach, 1991; Mirković et al., 2011). Morphological acquisition involves learning to integrate the multiple cues, so as to produce phonological representations of the appropriate inflected words (e.g., Thomas & Karmiloff-Smith, 2003). The output of the system of inflectional morphology is propagated to the articulatory system, which produces the inflected words (Hoeffner & McClelland, 1993).

It was assumed that all types of information are well developed when the acquisition of morphology commences. With respect to input and output phonology, this assumption entailed that the child has fully developed representations of the English phonemes and the phonological form of words before learning to inflect words. With respect to lexical semantics, it was assumed that the child has fully developed representations of the meaning of individual words, or at least knowledge of individual word forms. With respect to grammatical class, it was assumed that the child knows the syntactic distinctions between different word classes, such as nouns, verbs, or adjectives. Finally, with respect to target inflection it was assumed that the child has knowledge of the semantic distinctions between different grammatical features, such as the tense of verbs, the aspect of verbs, the number of nouns, the case of nouns, or the comparison of adjectives. In many cases, these represent simplifications, as some of these sources of information have more extended developmental time courses. From an explanatory point of view, each type of information needs its own developmental account. The MIG was neutral to the details of these subsidiary accounts, though we note some debates exist. For example, Pinker (1984, 1994) proposed that grammatical categories are innate, while Schlesinger (1988) argued that they emerge from semantic categories (e.g., objects vs. action).

Assumptions and simplifications relevant to the linguistic environment

The increase in complexity of languages and inflectional paradigms occurred at the expense of some simplifications to the training sets. Following other studies, such as Plunkett and Marchman (1991, 1993, 1996), Thomas (2005), and Thomas and Karmiloff-Smith (2003), the two training sets used in the model were based on artificial languages that approximated the main phonological, morphological, and statistical characteristics of English and Modern Greek inflectional morphology whilst keeping the scale of the model tractable. The MIG assumed a single phase of training referring to the production of appropriately inflected forms, unlike models considering multiple phases of learning (‘speaking’, ‘hearing’, ‘repeating’, and ‘generating’; see Joanisse, 2004; Joanisse & Seidenberg, 1999; Woollams et al., 2009). The architecture was trained with the full set of mappings from the onset of training, in a non-incremental fashion. This simplification allowed us to avoid the need for additional simulations to control for effects of the initial composition of the training set. Incremental training has its strongest effects on the very earliest phases of development, whereas our target phenomena lay beyond this phase, where there is little difference between incremental and non-incremental training regimes.

In the English version of the model, the artificial language consisted of a vocabulary of base forms belonging to three grammatical classes (nouns, verbs, and adjectives). The training set comprised mappings describing all possible inflections for all words within each grammatical class. The mappings were constructed to reflect statistical features of English morphology, including the relative frequency of grammatical classes and the frequency of allomorphic categories within inflections. These statistical features were derived from measurements on the tagged Brown corpus (Francis & Kučera, 1982), under the assumption that this collection of written documents could offer a reasonable approximation of the linguistic environment of the child (for a discussion, see Plunkett & Juola, 1999, p.467-468). More detailed accounts of morphological development should, of course, include constraints derived from child-directed corpora. The tagged Brown corpus (Francis & Kučera, 1982) was also used to derive measurements for other statistical characteristics of English, such as the frequency of inflections of nouns and verbs, or the frequency of the progressive or the past tense of verbs. These constraints were incorporated in a probabilistic training regime, which modulated the extent to which the network was exposed to inflections of different grammatical classes and inflections within a grammatical class accordingly. Similar type-frequency schemes have also been implemented in other models considering the acquisition of multiple inflections (Hoeffner & McClelland, 1993; Mirković et al., 2011; Plunkett & Juola, 1999). Finally, token frequency was considered through a highly simplified two-level scheme involving two levels (1 and 3 for low and high frequency regular mappings, and 6 and 9 for irregulars, like be/was correspondingly; after Thomas & Karmiloff-Smith, 2003).

In the Modern Greek version of the MIG, the artificial language could not include base forms as such forms do not exist in the language. For this reason, it considered stems corresponding to nouns, verbs, or adjectives. The training set consisted of stem-to-inflected-form mappings describing all the possible inflections applying to each stem. Constraints on the statistical characteristics of the system of morphology in Modern Greek were obtained from measurements on the Hellenic National Corpus (Hatzigeorgiu et al., 2000) and descriptions in grammars and psycholinguistic studies (e.g., Stephany, 1997); in the absence of data, certain constraints were made parallel to the English training set.

Architecture

The basic architecture used in the two versions of the MIG is depicted in Fig. 1. It is a three-layered feed-forward neural network (Plunkett & Marchman, 1991, 1993, 1996; Thomas & Karmiloff-Smith; 2003) in which four types of information or cues were presented in the input layer: (Input) Phonology; Lexical Semantics; Grammatical Category, and Target Inflection. The latter indicated the type of morphological modification that the network should perform on the base form (for English) or stem (for Modern Greek) presented in the input layer of the network. The network was expected to use the four input cues to produce the phonological form corresponding to the appropriate inflected form in the output layer (Output Phonology).

Fig. 1 also includes examples of input-output mappings from the English (light grey frames) and the Modern Greek (dark grey frames) training sets. In the example from English, the network produces the plural 'cats'; in the example from Modern Greek, the network produces the 2nd person singular of the perfective past tense for the verb 'to fall' (E-pe-ses). These examples make reference to the representational formats considered for the different types of information employed in the architecture and illustrate the key differences between the two versions of the MIG. These issues will be addressed in further detail in the following sections. At this point, we just note that the difference between the two versions of the MIG lay in the representations for Input and Output Phonology and Target Inflection (indicated by the dotted circles in Fig. 1).

Representations of linguistic information

Phonology

The English version of the MIG employed a distributed encoding scheme for phonemes from Thomas and Karmiloff-Smith (2003). This scheme was based on Fromkin, Blair, and Collins (2002, p.242-259) and encoded 42 phonemes, 24 consonants and 18 vowels, using 19 articulatory features. The mean Euclidean distance between representations of different phonemes was 1.9 bits. The Modern Greek version model considered a similar scheme of phonological representations, based on 21 articulatory features (Arvaniti, 2007). The distinguished 33 phonemes, 28 consonants and 5 vowels, with a mean distance of 1.9 bits.

Both base and inflected forms were encoded as sequences of phonemes, with each phoneme corresponding to a particular position (slot) of a slot-based scheme. In the English version of the model, words were monosyllabic and were accommodated in a five-slot scheme employed in both the input and output layer of the network (5*19=95 units; see Fig. 1). The first three phonemes were accommodated in the first three slots. These phonemes could correspond to triphonemic base forms (templates: CCV, VCC, and CVC; C=Consonant; V=Vowel), irregular inflected forms (same templates as for triphonemic base forms). The last two slots were used to accommodate, with right alignment, inflectional suffixes. This applied only to output phonology.

In the Modern Greek version of the model, the slot-based scheme considered 11 slots (11*20=220 units, see Fig. 1) aiming to accommodate multisyllabic words ranging from 2 to 5 syllables. Nouns, verbs, and adjectives in Modern Greek are rarely monosyllabic and bear syllabic stress in one of the last three syllables (Stephany, 1997). Syllabic stress is involved in the distinction of conjugational categories, as well as the formation of certain inflected forms (Stavrakaki & Clahsen, 2009). Based on these observations, word stems in the Modern Greek version of the MIG consisted of a full syllable and one or two consonants corresponding to the onset of a second syllable. The first syllable (templates: V, CV, and CCV) was accommodated in slots 2 to 4 and the stem ending in slots 5 and 6, both with right alignment. The first position of the slot-based scheme was used to accommodate a syllabic augment E- involved in the formation of the perfective and imperfective past tense (see Table 2), while slots 7 to 12 accommodated inflectional suffixes corresponding to different inflections (templates: V, VC, VCV, VCVC and VCVCVC) with right alignment. Importantly, phonological representations in the Modern Greek version of the model included three additional units to represent the syllable bearing stress, with localist encoding (e.g., 001 encoded stress on the last syllable). For Input Phonology in particular, which did not the include full word forms, these units described the stress pattern of the nominative singular for nouns and adjectives, and the first person of the present tense for verbs.

Lexical-semantics

Lexical-semantics were represented with localist encoding, following Joanisse and Seidenberg (1999) and Thomas and Karmiloff-Smith (2003). The English and the Greek version of the MIG were both based on a vocabulary of 1600 triphonemic base forms. Therefore, 1,600 units of the input layer were used to encode an equal number of nouns, verbs, and adjectives lemmas.

Grammatical Category

Grammatical category was represented uniformly in the two versions of the MIG with three units encoding locally the membership in the grammatical class of nouns, verbs, and adjectives.

Target Inflection

Target inflection representations encoded the inflections that were possible in each of the two systems of IM. In the English version of the model, 7 units were used to encode in a localist manner 7 types of inflections: the plural number of nouns, the possessive case of nouns, the 3rd person singular of verbs, the progressive of verbs, the past tense of verbs, the comparative of adjectives, and the superlative of adjectives. Base-form-to-base-form mappings were implemented as null inflections for all grammatical classes (all target inflection units set to zero).

In the Modern Greek version, 20 units were used to encode the targeted inflection as follows: 6 units for the localist encoding of person-number combinations (for verbs); 3 units for the localist encoding of tense (for verbs, see Table 2); 6 units for the localist encoding of case-number combinations (for nouns and adjectives): 3

units for the localist encoding of gender (for nouns): and 2 units for the localist encoding of the base or the comparative (for adjectives). Target inflection representations were thus sparsely distributed, in the sense that they concatenated several localist codes (e.g., person-number and tense for verbs).

Linguistic environment

In both the English and Modern Greek version of the model, the linguistic environment to which the architecture was exposed resulted from the combination of a training set, which included mappings describing inflections in the corresponding morphological system, and a probabilistic training regime, which ensured that the network was exposed to different inflections according to their frequency in the language. Figures 2 (English) and 3 (Modern Greek) show the structure of the linguistic environment for the two versions of the model. The coupling of the training sets with a probabilistic training is illustrated using 'wordle' graphs, developed using an online freeware tool (WordItOut, www.worditout.com). Wordle graphs depict the variety of types of mappings in the two training sets in the number of tags they contain. At the same time, they depict statistical properties, with font size indicating the frequency of each inflection type (tag).

An inspection of Figures 2 and 3 reveals that the English linguistic environment presented a much simpler structure than the Modern Greek linguistic environment. Base forms, especially of nouns, were statistically dominant in the English version of the MIG (top graph in Fig. 2). The middle and the bottom graphs in Fig. 2 depict the quasi-regular structure of the English past tense and plural, correspondingly. The relative frequency of irregular mappings was higher in the past tense than in the plural.

The complexity of the linguistic environment in the Modern Greek version of the model (Fig. 3) is reflected in an increased number of tags, compared to the English version. In the absence of default forms, differences between inflection types in terms of frequency are more even. The lower graph in Fig. 3 focuses on the perfective past tense. Even when a subdomain of Modern Greek is considered individually, there is still a great deal of complexity (compare with middle graph in Fig. 2), arising from the combination of different conjugational classes with different persons and numbers.

Training Sets

The two training sets consisted of exemplars in which input phonology, lexical semantics, grammatical class and target inflection representations mapped to output phonology. Both training sets included inflections for a vocabulary of 1600 words: 800 nouns, 400 verbs, and 400 adjectives. The distribution of words in different grammatical classes was constrained by measurements of the tagged Brown Corpus (Francis & Kučera, 1982); in the absence of relevant data the same distribution was also used in the Modern Greek training set, since the number of nouns, verbs and adjectives is broadly constrained by the topics that people talk about.

The English training set included base-form-to-base-form mappings and mappings corresponding to all inflections shown in Table 2, apart from the past participle, which was not distinguished from the past tense for reasons of simplicity. We omitted the phoneme /s/ in the –est suffix of the superlative, a simplification purely for implementation, to allow the suffix to fit in two slots. The distribution of mappings was such to include constraints on the frequencies of allomorphic categories (past tense: -/t/ : /d/: /ed/ = 65 : 180 : 85); regular and irregular categories (past tense: 330 regulars and 70 irregulars); and clusters within irregular mappings (e.g., irregular past tense: 50 vowel change; 10 arbitrary[1]; 10 identity). These constraints were based on measurements of the tagged Brown corpus (with the NLTK software; Bird, Klein, & Loper, 2009). For the full vocabulary and all inflected forms, the English training set consisted of 5,200 mappings.

The Modern Greek training set included a significantly greater degree of complexity. Verbs were inflected as shown in Table 2. Verb stems were divided in conjugational classes (150 verbs in class 1; 40 in class 2a; 10 in class 2b; 200 in class 3, based on descriptions in Stavrakaki & Clahsen, 2001) and were inflected with respect to person and number in the present tense, the imperfective past tense, and the perfective past tense. Similarly, nouns were assigned grammatical gender, divided in conjugational classes (5 classed for masculine; 4 for feminine; and 5 for neuter), and then inflected in the nominative, genitive, and accusative case of the singular and plural number. Adjectives (4 classes) were inflected similarly to nouns and additionally with respect to gender in both base and comparative. The Modern Greek training set included 26,400 mappings, i.e., around 5 times more mappings than the English training set.

Probabilistic training regime

The probabilistic training regime modulated the extent to which the network was exposed to different types of inflections. For example, for mappings describing noun inflection in English, the ratio *base form : plural : genitive* was set to 60 : 15 : 5 (based on measurements on the tagged Brown corpus, Francis & Kučera, 1982,

[1] There are only two verbs with arbitrary past tenses in English. We considered a larger number of this type of mappings to allow finer graduations of performance (see also, Thomas & Karmiloff-Smith, 2003, p.660).

using the NLTK software; Bird et al., 2009). Similarly, in the Modern Greek version, the frequencies of different person-number combinations and the three tenses were based on measurements of a sample of the first 30 verbs in a randomly chosen snippet of the HNC (e.g., 1st sing : 2nd sing : 3rd sing : 1st plur : 2nd plur : 3rd plur = 1 : 1 : 4 : 1 : 1 : 2; present : imperfective past : perfective past = 5 : 2 : 3). Sampling of the HNC was chosen in the absence of a tagged corpus of Modern Greek.

Generalization set

Generalization sets were developed to measure the extent to which the network was also able to apply inflectional rules on novel items. Generalization sets included rhymes of existing verbs, which were presented to the network with the same grammatical class and target inflection representations but with a null lexical semantics representation (all units set to zero). The English generalization set consisted of three subsets of novel base forms of varying degree of similarity to base forms of the training set. This was to address the effects of phonological similarity on novel-item inflection (Prasada & Pinker, 1993). In the high-similarity subset rhymes shared the last two phonemes with existing base forms; in the medium-similarity subset rhymes and existing base forms were similar only in the last phoneme; in the low-similarity subset rhymes and existing base forms shared the last phoneme, while the first two phonemes of the novel items were such that they did not follow the CVC, VCC, CVV templates used in existing items and so were phonotactically illegal. In the Modern Greek version of the model, the generalization set consisted of novel items sharing stem endings with existing stems.

As discussed earlier, the MIG focused on a regular generalization, i.e., we examined whether novel items were inflected similarly to existing items they rhymed with. We did not consider whether irregular rhymes were inflected irregularly.

Simulation design and evaluation

We performed ten replications with each version of the model, training networks that employed 100 units in the hidden layer in the English version of the model and 200 units in the Modern Greek version. The number of hidden units was selected based on pilot simulations, as it was found sufficient to allow the network to learn all the mappings of the two training sets. We used more hidden units in the Modern Greek version of the MIG because the sheer number of input and output units was greater compared to the English version.

Network weights were initialized in the interval [-1, 1] using random seeds. They were trained based on the back propagation algorithm (Rumelhart, Hinton, & Williams, 1986) with the cross-entropy learning criterion (Hinton, 1989), a pattern-update schedule, and a learning rate of 0.01. Networks were trained for 400 epochs with a non-incremental training regime.

In each epoch, networks were presented with 1600 mappings, i.e., equal to the vocabulary size of the artificial language. The two versions of the model were thus aligned in terms of their exposure to the linguistic input, to correspond to the intuition that both children acquiring English and Modern Greek as a first language are exposed a similar sheer volume of inflectional mappings. Note, however, that this challenged the acquisition of the Modern Greek training set as in each epoch, the architecture was exposed to only ~6% of its mappings, compared to ~31% in the English version.

Networks were tested on the training and generalization set at the end of each epoch. For each mapping of these test sets, the output of the network was evaluated by translating the activation pattern in each slot of the output layer to a phoneme using a nearest neighbor algorithm. In the English version of the MIG, the strings that were obtained by this procedure were categorized to general classes of responses based on the psycholinguistic literature and preliminary observations of the output (e.g., past tense: correct, omission error, overgeneralization, wrong stem/correct suffix). Incorrect responses that were not captured in these categories were classified as ‘other’. In the Modern Greek version, the categorization of output strings needed to be more fine-grained, in order to deal with the complexity and the fusional nature of the language. The defined categories described combinations of alternative responses relevant to individual features combined in a single word forms. For example, for mappings falling in the perfective past tense in conjugational class 1: Multiple error types described possible problems in the application of the sigmatic rule, combined with possibilities for errors in the suffix for person and number.

The evaluation procedure produced detailed developmental trajectories for correct responses and error patterns in different inflections, which additionally took into account fine-grained distinctions of types of mappings within a given inflection type, such as tokens of high and low-frequency, allomorphic regular paradigms, tokens of different conjugational classes, and combinations of these. In this way, the output of the model was comparable to developmental data.

Qualitative comparisons identified general similarities and differences based on observations of whether the model overestimated or underestimated rates of correct responses or error patterns relevant to particular target empirical phenomena. In many cases (see Tables 4 and 5), quantitative comparisons were also possible. Such comparisons were made by calculating the Pearson’s correlation coefficient value and its significance level (two-tailed) between vectors corresponding to the model’s output and empirical data, after the model and the data were matched on certain aspects of the data (e.g., 90% accuracy for acquisition; Brown, 1973;

accuracy on regular items for the data of van der Lely & Ullman, 2001). Correlations between vectors were used because evaluation involved simultaneous comparisons between multiple measures from the model and from the empirical data. We took correlation coefficients greater than 0.8 and with a significance value less than 0.05 to imply quantitative similarities; correlation coefficients greater than 0.8 and significance value greater than 0.05 to imply qualitative similarities; otherwise the model's output was dissimilar to empirical data. These criteria provided a strict and objective method for model-data comparison.

Results

Results from the English version of the MIG

Learnability of the English training set

Fig. 4 (continuous thick line) shows the overall accuracy of the network in the mappings of the English training set during the 400 epochs training time. Thin lines around it depict variability in accuracy rates in individual simulations. The network reached ceiling performance and overall accuracy rates exceeded 99% at the end of training. Multiple inflection types of multiple grammatical classes were therefore learnable by the neural network architecture of Fig. 1. The remainder of this section examines the extent to which these inflections were also acquired in a psycholinguistically plausible manner with reference to target empirical phenomena ENG1 to ENG5.

Insert Fig. 4 about here

Target empirical phenomenon ENG1: Order of Emergence

Fig. 5 depicts accuracy rates for different noun, verb, and adjective inflections during the first 200 epochs of training along with Brown's (1973) criterion for acquisition (horizontal horizontal line at 90%). Table 5 focuses on a subset of inflections that were included in the studies of Brown (1973) and de Villiers and de Villiers (1973) ordered by their type frequency (second column). The third column of this table includes a simplified four-level scheme characterizing inflections in terms of their morphological complexity (1: fully regular, non-allomorphic; 2: fully regular, allomorphic; 3: regular part of quasi-regular domain, allomorphic; 4: irregular), while the last three columns provide the order of acquisition in the empirical data and the MIG.

Insert Fig. 5 about here

Insert Table 5 about here

Using the same criterion for acquisition, the correlation coefficient between the rank order of acquisition in the MIG (last column of Table 5) and the rank order in Brown (1973) (fourth column) was $r(6) = 0.77$, $p = 0.07$; the coefficient between the rank order in the MIG and the rank order in de Villiers and de Villiers (1973) (fifth column) was $r(6) = 0.67$, $p = 0.14$; the coefficient between the rank orders in Brown (1973) and de Villiers and de Villiers (1973) was $r(6) = 0.90$, $p = 0.01$. According to the criteria for the evaluation of quantitative comparisons, the MIG fitted qualitatively the pattern of Brown (1973) but was dissimilar to the pattern of de Villiers and de Villiers (1973). The two sets of human data were, however, quantitatively similar to each other.

Qualitative similarities between the model and the empirical data were more pronounced in the acquisition of regular inflections or regular subtypes within quasi-regular inflections. The main discrepancy between the model and the human data appeared in the acquisition of the irregular past tense. This was the last to present accuracy rates over 90% in the MIG, unlike the empirical data. Arguably, this discrepancy stems from its training on the full range of the rare category of irregular mappings from the onset of the training time (not considering a set of early, mainly irregular verbs; Rumelhart & McClelland, 1986). It could be addressed in future versions of the model using incremental training regimes (see Plunkett & Juola, 1999; Plunkett & Marchman; 1993, 1996). When the irregular past tense was excluded from the comparisons between the model and empirical data, the acquisition of inflections in the MIG was quantitatively similar to the human data [correlation coefficients: $r(5) = 0.90$, $p = 0.04$ for Brown, 1973; $r(5) = 0.93$, $p = 0.02$ for de Villiers & de Villiers, 1973].

Turning to the rank order of inflections in terms of type frequencies or their ranking for morphological complexity, the rank order of type frequencies was dissimilar to the order of acquisition in both the model and the empirical data [correlation coefficients: $r(6) = 0.25$, $p = 0.62$ for Brown, 1973; $r(6) = 0.32$, $p = 0.54$ for de Villiers & de Villiers, 1973; and $r(6) = 0.49$, $p = 0.33$ for the MIG]. The same held for the rank order of morphological complexity [correlation coefficients: $r(6) = 0.36$, $p = 0.49$ for Brown, 1973; $r(6) = 0.16$, $p = 0.77$ for de Villiers & de Villiers, 1973; and $r(6) = 0.76$, $p = 0.08$ for the MIG]. This suggested that the order of acquisition in both the MIG and the human data involved the integration of multiple statistical properties of the linguistic environment.

Target empirical phenomenon ENG2 to ENG5: The profile of the English past tense

Figures 6 and 7 present the learning profile of regular and irregular past tense in the empirical data from van der Lely and Ullman (2001) and the MIG. The human data provide developmental trajectories for correct responses, omission errors, and irregularized forms in regular inflection (Fig. 6a), and correct responses, omission errors, and overgeneralizations in irregular inflection (Fig. 7a). Figures 6b and 7b depict the output of the MIG in the regular and irregular past tense (correspondingly). The model captured the main error patterns in van der Lely and Ullman (2001), namely omission and overgeneralization errors and, similarly to the data, did not produce irregularized responses in regular inflection. The output of the model in regular inflection also included responses in which root forms were suffixed with wrong past tense allomorphs, and responses where past tense suffixes were applied to stems that were reproduced inaccurately in the output layer. It is possible that such responses are treated as correct responses in experimental tasks (experimenter perceptual biases). However, here they were classified in separate categories, namely substitution errors, and wrong stem/correct suffix errors. With regards to irregular past tense, apart from omission errors and overgeneralization, the output of the model also included blend errors, as well as other non-suffixed forms. Other non-suffixed forms included responses that were neither omission errors nor correct irregular forms. Similarly to regular inflection, it is likely that some of these responses were treated as correct responses or omission errors in experimental tasks -however, here they were treated as a separate category. Blend errors were produced in lower rates than overgeneralization errors, in line with Marcus et al. (1992). Further, overgeneralization errors were produced in lower rates in the past tense than in noun plural (Marchman et al., 1997).

Insert Fig. 6 about here

Insert Fig. 7 about here

The comparison of human data and simulation results in Fig. 6c (regular past tense) and 7c (irregular past tense) was performed after the model was matched to the data on accuracy in regulars. Substitution errors, wrong stem/correct suffix errors, blend and other (non-suffixed) errors were excluded in the absence of evidence of how such forms were treated in van der Lely and Ullman (2001). The correlation coefficient between vectors corresponding to human performance and the modeling results, plotted in Figures 6c and 7c, was $r(9) = 0.96$, $p < 0.001$ for regular inflection and $r(9) = 0.90$, $p = 0.001$ for irregular inflection. Therefore, the model fitted quantitatively the data of van der Lely and Ullman (2001) with regards to target empirical phenomena ENG2 and ENG3.

Despite the quantitative match, two limitations should be noted. First, the model produced omission errors in consistently lower rates than children, especially in regular inflection. The second limitation of the model is that irregulars were inflected less accurately than the children. Interestingly, both these limitations were not presented when substitution errors, wrong stem/correct suffix errors, blend and other (non-suffixed) errors were included in the categories of correct responses for regulars and irregulars, suggesting that experimenter perceptual biases might indeed be strong in inflection production tasks.

The data from van der Lely and Ullman (2001) were also used to address the interaction between token frequency and regularity across development (target empirical phenomenon ENG4). The correlation coefficient between two 6-element vectors (3 stages x 2 values for regularity) for frequency effects (accuracy in high frequency – accuracy in low frequency verbs) in the MIG and the empirical data was $r(6) = 0.83$, $p = 0.07$, suggesting a qualitative match between the model and the data.

More generally, frequency-by-regularity interaction in the MIG presented three main stages (see also Ellis & Schmidt, 1998). At an early stage of language acquisition (younger group in van der Lely & Ullman, 2001), frequency effects were equally large for regular and irregular mappings. At an intermediate stage (middle and older group in van der Lely & Ullman, 2001), frequency effects were more pronounced for irregulars than for regulars. Finally, at a late stage (epoch 250 and afterwards) accuracy rates for both regular and irregular inflections were at ceiling levels (over 95%) and frequency effects for both regular and irregulars were small.

Finally, the output of the MIG was evaluated on the inflection of novel items (target empirical phenomenon ENG5). In general, the model preferred rule-based inflection of novel rhymes and this preference was contingent on phonological similarity between novel and existing items (Prasada & Pinker, 1993). In the regular past tense, the rates of rule-based inflection (e.g., wug/wugged) at the end of training were around 88% for novel items in the high-similarity generalization subset, and 87% for items in the intermediate-similarity generalization subset. These rates were not as high (around 54%, at the end of training) for items in the low-similarity generalization subset, i.e., phonotactically illegal non-words. However, inflectional suffixes were applied. A percentage of responses were wrong stem/ correct suffix errors, i.e, the correct suffix was applied to a root form that was not reproduced correctly (e.g., wug/wagged, around 33% at the end of training). Such responses were taken to signify the difficulty of the network in reproducing unusual forms than applying inflectional rules. This is a difficulty that one would expect also in children and adults akin to repeating bizarre non-words (e.g., Gallon, Harris & van der Lely, 2007). Taken together, the model responded with a regular suffix to 87% of novel items that were dissimilar to those in its training set.

Comparisons of the model output and the data of van der Lely and Ullman (2001) on the inflection of novel items were performed with the model being matched to the human data based on accuracy in existing regulars and focusing on the inflection of novel rhymes. The correlation coefficient between vectors corresponding to the matched data suggested a quantitative fit, $r(9) = 0.91$, $p < 0.001$. However, compared to the empirical data the model produced fewer omission errors than expected.

Results from the Modern Greek version of the MIG

Learnability

Fig. 4 shows overall accuracy of the MIG in the mappings of the Modern training set (thick dotted line). Thinner lines surrounding this line correspond to results from the 10 replications. The model learnt the Modern Greek training set with rates of correct responses over 98.5% in epoch 400. Further training for an additional interval of 100 epochs was also considered, to ensure the convergence to ceiling levels. By 500 epochs, accuracy levels had exceeded 99%. The learnability of the Modern Greek training set by the MIG suggested the ability of the model to acquire a notably larger and more complex training set than the English version of the model (25,600 vs. 5,200 mappings), using the same computational architecture.

Accuracy rates in the Modern Greek version of the MIG were consistently lower than accuracy rates in the English version at any given point in training. Apart from the stark contrast between the two training sets with respect to size and complexity, these differences are likely due to the alignment of the two models in terms of the sheer volume of mappings to which the two architectures were exposed in each epoch. In general, the pattern of lower accuracy rates in the Modern Greek training set was not consistent with evidence from the cross-linguistic morphological acquisition. Although detailed cross-linguistic comparisons of the ages at which different inflections emerge in English and Modern Greek are beyond the scope of this paper, we can illustrate the general pattern in the cross-linguistic language development using an example from Stavrakaki and Clahsen (2009) and van der Lely and Ullman (2001). In the perfective past-tense production task considered in Stavrakaki and Clahsen (2009), rates of correct responses in the sigmatic category were over 90% at 6;4 ; in the English past tense production task of van der Lely and Ullman (2001), accuracy rates in regular inflection were 72.4% at 6;11.

The MIG could reproduce accuracy rates in the Modern Greek training set that were equal to or higher than corresponding rates in the English training set either by increasing the number of training experiences per epoch, or increasing the computational resources (hidden units) in the system. A greater recruitment of processing resources in response to a more complex domain could be achieved within a constructivist framework (Ruh & Westermann, 2009). Here, we can simply note that the cross-linguistic pattern for overall accuracy in the MIG suggest increased processing requirements for the acquisition of IM in Modern Greek. This prediction could be investigated using neuroimaging methodologies and constructivist artificial neural networks.

Target empirical phenomena related to analogues of the Optional Infinitive stage: GR1, GR5, GR8

When acquiring nominal and verbal inflection, the MIG generated error patterns symptomatic of responses produced by the children during early developmental stages, associated with the inability to mark contrastively various grammatical features, such as case, person, and number (Stephany, 1997). Similar to the empirical data, these responses differed across grammatical classes and corresponded to the overgeneralization of highly frequent forms within each grammatical class to examples where other forms were appropriate. As shown in Fig. 8, the acquisition of the genitive singular of neuter nouns presented high rates of forms corresponding to nominative or accusative forms of the same or other conjugational classes .As shown in Fig. 9, the acquisition of verbs featured high rates of i-forms. Similar to the empirical data (Stephany, 1997; Varlokosta et al., 1996), the highest percentages of i-forms occurred in the 2nd person of the singular number, demonstrating that their occurrence was conditioned by phonological overlap with the target response.

Insert Fig. 8 about here

Insert Fig. 9 about here

Target empirical phenomena related to the order of emergence of grammatical features: GR2, GR3, GR4, GR6, GR7, and GR9

The MIG captured the general patterns for the order of emergence of different grammatical features described in target empirical phenomena GR2, GR3, GR4, GR6, GR7, and GR9. Fig. 10 presents results on the acquisition of the three genders of nouns, the acquisition of case and number in nouns, and the acquisition of the genitive case in the different conjugational classes of nouns (correspondingly). These patterns were identical with the relevant empirical data.

Insert Fig. 10 about here

We should note, however, two important limitations of the model in addressing phenomena relevant to the order of emergence of different grammatical features. The first limitation concerned the presence of crossovers in the lines corresponding to accuracy rates in different grammatical features. One such crossover is shown in Fig. 10a. Accuracy rates in feminine nouns were slightly higher than accuracy rates on neuter nouns in the early epochs of training; however, this pattern was reversed after epoch 90. Similar crossover patterns were not reported in the empirical literature. Crossovers were taken to indicate an interaction between the effects of frequency and mapping complexity in driving the behavior of the model and the gradual acquisition of more latent regularities. In this particular case, although neuter noun mappings were more frequent, their accuracy rates were lower than accuracy rates of feminine nouns in the early epochs of training because they presented a more complex structure (e.g., four sets of plural suffixes in the neuter gender, compared to three sets in the feminine gender).

Target empirical phenomenon related to developmental error patterns: GR10

Figures 11 and 12 compare the modeling output to the behavioral data of Stavrakaki and Clahsen (2009) for the acquisition of the perfective past tense for two main classes of verbs, the sigmatic and the non-sigmatic. Empirical data came from a perfective past-tense elicitation task focusing on the 3rd person singular. The modeling output was analyzed focusing on the 2nd person singular. The reason why the 2nd rather than the 3rd person singular was selected for the analysis of the simulation output was that it allowed consideration of a particular error type not presented in the 3rd person singular (see below).

Insert Fig. 11 about here

Insert Fig. 12 about here

There were several similarities between the simulation output and the human data with regards to accuracy rates and error patterns in the two categories of verbs. Accuracy rates were higher for sigmatic than for non-sigmatic verbs, and sigmatic responses were produced in the non-sigmatic category in higher percentages than non-sigmatic responses in the sigmatic category. A notable percentage of responses were imperfective past tense forms in both the model and the data. The fit of the model to the data was excellent in the sigmatic category; however, within the non-sigmatic category the model underestimated sigmatic responses and produced more ‘other’ responses.

When the model was matched to the empirical data on accuracy in the sigmatic category, the correlation coefficient between the simulation results and the data of Stavrakaki and Clahsen (2009) was $r(21) = 0.98$, $p < 0.001$ in the sigmatic category and $r(21) = 0.92$, $p < 0.001$ in the non-sigmatic category. Therefore the model quantitatively fitted the behavioural data. In addition, a quantitative fit was also possible for the data of Stavrakaki and Clahsen (2009) for the inflection of rhymes of existing sigmatic, $r(21) = 0.90$, $p < 0.001$, and non-sigmatic, $r(21) = 0.95$, $p < 0.001$ verbs.

Overgeneralization of 3rd singular perfective past-tense forms. An interesting difference between the simulation results and the human data concerned the incorrect production of 3rd singular perfective past-tense forms, in the first epochs of training (Fig. 11b). These forms could correspond to S-V agreement errors in the perfective past tense, i.e., responses in which the perfective past tense but not the person has been marked correctly. As S-V agreement was not considered in the perfective past-tense elicitation tasks employed in Stavrakaki and Clahsen (2009), the targeted empirical data did not include responses of this type. The MIG, nevertheless, predicted that this type of error should be observed in studies examining perfective past-tense formation in younger children. Another prediction was that the rates of these errors would be higher in the 2nd person singular, which presented a high degree of phonological overlap with the 3rd person singular. Although these are novel predictions of the model, the latter pattern was consistent with an analysis in a case study by Clahsen and Dalalakis (1999) for the language of a Greek child with SLI. Further empirical evidence is warranted.

An analysis of the emergent functional architecture of the MIG

The results from the simulations suggested that the MIG learnt training sets corresponding to fully-fledged morphological systems similar to English or Modern Greek in a way similar to the acquisition of the two languages. This was achieved through the integration of different cues in a flexible manner, i.e., with different types of information being weighted together to determine inflection, with different cues more important for the learning of particular types of inflectional paradigms. The integration of cues was also highly contingent on the statistical characteristics of the two different linguistic environments. We investigated the progression of this process within and across the two languages by observing how the mean amplitude of weights from input units to the hidden layer, related to particular cues or mappings, changed across training time. This provides an insight into the emergence of a particular structure in the network supporting the acquisition of different inflectional paradigms. It also shows the cross-linguistic generality of the model. MIG allows for the emergence of different functional architectures for different languages. By contrast, the dual-route model (e.g., Marcus et al., 1992; Pinker, 1984, 1994, 1995, 1999; Pinker & Ullman, 2002) is only appropriate to languages presenting a dichotomy between regular and irregular inflection (e.g., English).

English version of the MIG

Fig. 13 shows the progression of mean weight amplitudes corresponding to the four major cues across the training time in the English version of the MIG. Weights from target inflection units to the hidden layer had consistently the largest mean amplitude value. This pattern confirmed the obvious importance of this cue in determining inflection. Weights from input units corresponding to phonology had moderate values of mean amplitude, which were larger than the mean amplitude of weights corresponding to lexical semantics; the latter remained relatively constant across training. Of the four cues presented in the input layer, weights corresponding to the three grammatical class units had the lowest mean amplitude value. In the MIG this cue was not particularly important in inflection, verified by simulations in which grammatical class information was omitted with no effect on developmental performance. In a sense, grammatical information was redundant, as it was encapsulated in target inflection information: when the network was asked to produce the past tense, this also implied that the item to be inflected was a verb.

Insert Fig. 13 about here

Fig. 13b presents the mean weight amplitude from the seven target inflection units for the English MIG. The lowest mean amplitudes corresponded to units encoding the plural and the genitive of nouns, as well as the 3rd singular of verbs. These three inflections shared the use of the -s suffix and its allomorphs. The -s suffix was the most common of the inflectional suffixes and applied to a wide range of regular mappings of nouns and verbs. The lower values of weight amplitudes could be due to these units being less informative than other target inflection units, in the sense that they predicted the most common morphological modification. Consistent with this observation, larger mean amplitudes were exhibited in the weights from the units encoding the comparative and the superlative of adjectives, the inflections that were less frequent in the training set. Activation of these input units needed to override more common or ‘default’ behavior.

Finally, although the average amplitude value of weights from input units encoding lexical semantics was relatively low and constant across training, the amplitude of these weights was highly contingent on whether these corresponded to lexical items that were regular or irregular[2]. As shown in Fig. 13c, weights from units encoding irregular items were generally stronger than weights from units encoding regular items. This difference was more pronounced within the class of verbs, possibly because the irregular cluster was more frequent within this grammatical class. The difference emerged after epoch 35, i.e., it coincided with the observation of non-zero accuracy rates in irregular mappings after this epoch (see Fig. 5). Consistent with Joanisse and Seidenberg (1999), the MIG exhibited an emergent involvement of lexical semantics in irregular inflection. This was confirmed in simulations where we omitted the lexical semantics cue. The absence of lexical semantics information resulted in pronounced deficits in irregular inflection, compared to the baseline model.

The finding that weights from lexical semantics to the hidden layer were modulated by regularity suggested an emergent bipartite structure with similarities to that postulated by the dual-route model (Marcus et al., 1992; Pinker, 1984, 1994, 1995, 1999; Pinker & Ullman, 2002). The trained version of the MIG encapsulated two processes for the production of inflected forms. A regular inflection process relied heavily upon information on the phonological structure of a stem to be reproduced and combined (optionally, and as indicated by target inflection) with an appropriate suffix in the output layer of the network. An irregular inflection process, on the other hand, relied upon lexical semantics information, predicting idiosyncratic

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[2] Note that localist encoding allowed us to distinguish between lexical semantics units corresponding to regular and irregular items.

inflection for particular lexical items, and serving to block the operation of the regular process predicted by the other cues.

Modern Greek version of the MIG

Fig. 14 shows the progression of the mean weight amplitudes in the Modern Greek version of the model. Comparison of plots 14a, 14b, and 14c with the corresponding plots of Fig. 13 reveals how the linguistic environment of the two versions of the model altered the emergent functional architecture. As shown in plot 14a, the mean amplitude of weights to the hidden layer coming from the target inflection was higher that the mean amplitude of weights from all other cues. This was similar to the English version of the model. However, the mean amplitude of weights from target inflection input units was lower in the Modern Greek version (mean amplitude at the end of training =1, vs. 1.4 in the English version). A possible reason for this difference was the prevalence of base-form-to-base-form mappings attributing greater information content to the target inflection units.

Insert Fig. 14 about here

Fig. 14a shows mean weight amplitudes for units encoding input phonology, separating phonological information per se (articulatory features) and syllabic stress. Both parts of input phonology were important in inflection (moderate values of mean amplitude; similar to the English version). The distinction between articulation and syllabic suggested that stress information was particularly important, probably because the stress pattern underlay the assignment of lexical items to conjugational classes, and therefore determined the way items were inflected. Another important difference between the English and the Modern Greek version of the model was the high weights from units encoding grammatical class. In the English version of the model, the information provided by grammatical class was redundant, and incorporated within target inflection. In the Modern Greek version, grammatical class information was complementary to target inflection information. For example, it was important to determine whether a given pattern for case, number, and gender referred to the inflection of a noun or adjective. Weights to the hidden layer from units encoding grammatical class were therefore stronger in the Modern Greek version of the model than the English version.

The mean amplitude of weights from target inflection units corresponding to different grammatical features was modulated by the frequency of these features in the training set. Similarly to the English version, the higher the frequency of a given grammatical feature, the lower the information content of the corresponding part of the target inflection information and the amplitude of weights from the corresponding input unit to the hidden layer. Thus, the mean amplitude of weights from units corresponding to tense is higher than the mean amplitude of weights corresponding to case and number, because the former refer only to verb mappings while the latter refer to both noun and adjective mappings (Fig. 14b). In a similar manner, the mean amplitude of weights corresponding to different persons and number is higher for the first and the second person of the plural, which are less frequent. The emerging pattern is one of a system that learns ‘default’ or most frequent behaviors, and that uses strong weights to allow cues marking less frequent behaviors to override the default. Once more, the ethos of the dual-route model is present here (e.g., Marcus et al., 1992; Pinker, 1984, 1994, 1995, 1999; Pinker & Ullman, 2002). Finally, Fig. 14c analyses weights from input units corresponding to different conjugational classes of verbs to the hidden layer. The amplitudes of weights presented a graded pattern that reflected the type frequencies of the different conjugational classes. This pattern was different to the English version, due to the lack of a clear-cut dichotomy between regular and irregular inflection, reflecting the fact that a strict dual-route approach is not appropriate to highly inflected languages.

Discussion

The MIG set out to capture a wide range of empirical phenomena in the cross-linguistic acquisition of inflectional morphology. The model implemented a multiple-cue neural network architecture for a generalized inflectional system, which was exposed to simplified linguistic environments incorporating the main morphological characteristics of either English or Modern Greek. A principal research aim was to show that this model could be robust to interactions arising from the acquisition of multiple grammatical classes and multiple inflections of a class within the same processing architecture. This aim was addressed by evaluating the model against empirical data constraining the acquisition of fully-blown inflectional systems, as well as fine-grained developmental data for the acquisition of individual inflections (e.g., developmental error patterns of the past tense and the rates in which these occur). Another aim was to show that the MIG could be general across language typologies. Developing the Modern Greek version of the MIG challenged it to acquire a system of morphology with important differences from English, simulating a different range of developmental effects that describe its acquisition.

The two principal research aims of the MIG have not been previously addressed under the connectionist framework. Models of inflectional morphology have been primarily focused on the English past tense. A few models that included broader inflectional paradigms have been still limited, either to the study of the acquisition of a small number (e.g., Plunkett & Juola, 1999) of inflections from different grammatical classes or the acquisition of inflections within the same grammatical class (Hoeffner, 1992; Mirković et al., 2011).

With regards to the modeling of morphological development cross-linguistically, existing models of non-English inflectional morphology have mostly focused on languages presenting multiple conjugational classes and especially the phenomenon of minority-default inflection. These models employed architectures that were different from those used in of studies of English morphology. These architectures performed categorization to conjugational classes (Nakisa & Hahn, 1997; Plunkett & Nakisa, 1996) rather than inflection, or lacked phonological information in the input layer (Mirković et al., 2011). This was not the case for the MIG. The MIG is the first connectionist model with a strong commitment to a cross-linguistic and developmental perspective, in the sense that: 1) it employed the same architecture to address the acquisition of different language typologies; 2) the same set of modeling assumptions and simplifications applied to the representation formats and the development of the two training sets; 3) the two versions were aligned with respect to their exposure to inflectional mappings in each epoch of training time; and 4) the model was compared to corresponding developmental data from two languages based on similar constraints (e.g., Brown's criterion for acquisition, Brown, 1973; matching on accuracy on regular/sigmatic past tense).

It was no small challenge to establish the learnability of training sets corresponding to fully-fledged morphological systems in connectionist architectures. A greater challenge still, however, was to show that the architecture could also learn the two training sets in a psycholinguistically plausible manner. There were numerous ways in which the model could fail. It could produce behaviors that were not symptomatic of human development. This was because the two training sets, and especially in the Modern Greek version of the model, included a rich variety of inflectional mappings that might interfere with another. Nothing in our research design and the main assumptions of the model excluded the possibility that this variation would give rise to interactions resulting in responses that were psycholinguistically unrealistic, such as, commission errors (e.g., -s suffixes in the past tense). It is therefore important that the MIG simulated the target empirical phenomena in Tables 4 and 5, as well as that in many cases the model was robust to comparisons with the empirical data under a strict numerical criteria. It is also important that the model simulated the acquisition of two different language typologies based on assumptions and simplifications that were not specific to either language.

To model the acquisition of fully-blown morphological systems across languages, the MIG synthesized previous connectionist accounts of morphological development positing the involvement of different types of information in morphological production: phonology (Rumelhart & McClelland, 1986); lexical semantics (Joanisse & Seidenberg, 1999); grammatical class (Plunkett & Juola, 1999); and target inflection (Hoeffner, 1992). The model exemplified this multiple-cue account, showing how these four cues were integrated in a flexible manner across development to accommodate mappings from different inflections, different grammatical classes, or regular and irregular categories. The four cues were also integrated in a flexible manner across languages, supporting the cross-linguistic generality of the MIG. Finally, the use of multiple cues yielded high rates of rule-based inflection of items of the generalization sets, consistent with empirical data (e.g., van der Lely & Ullman, 2001).

The MIG also suggested a developmental trajectory for the emergence of a structure supporting a fully-fledged system for morphological production, and demonstrated differences in this structure across languages. These differences were related to major typological characteristics, such as the presence of common inflectional paradigms across grammatical classes (greater importance of the grammatical class cue in the Modern Greek version); or the presence of multiple conjugational classes (dichotomous/graded pattern for the importance of lexical semantics in the English/ Modern Greek version). Importantly, this structure presented similarities with the dual route model in the English version of the MIG but not in the Modern Greek version. This finding challenges the cross-linguistic generality of dual-route accounts of morphological development.

Another key theoretical assumption of the MIG was the importance of statistical regularities in the linguistic input in determining developmental patterns in morphological development. Both versions of the model included psycholinguistically motivated constraints for the structure of the linguistic environment. Such constraints determined the composition of the training set and training regime. They were sufficient to drive the learning of the network in ways similar to human data, despite the simplifications of the artificial language approach and non-incremental training in the MIG. These constraints were important for explaining empirical effects in morphological development captured by the model. For example, type frequency of different inflections was integrated with complexity to determine their order of acquisition. Statistical constraints for the linguistic environment also supported a unified explanation of a range of empirical phenomena in the acquisition of English and Modern Greek. For example, omission errors in the acquisition of English, and three error patterns particular to the noun, verb, and adjective grammatical classes in the acquisition of Modern Greek, were common patterns characterizing the early stages of acquisition and produced as a prototype effect of exemplars of high type frequency.

The successes of the MIG in simulating empirical effects in morphological development were not without shortcomings. For example, the English version underestimated the rates of omission errors in both the inflection of existing and novel items. The Modern Greek version of the model overestimated accuracy rates in the imperfective past tense. Although these shortcomings challenged the robustness of the model, they were not critical for its success in simulating the cross-linguistic morphological development, in the sense that it was possible to identify their origin in the assumptions and simplifications of the model and possible to suggest minor modifications to overcome these.

More important are, perhaps, other limitations related to major simplifications inherent in the research design of the model. These limitations need to be addressed to achieve a more plausible computational model of morphological development. For example, despite the fact that the MIG implemented a remarkably broader morphological paradigm than other models of inflectional morphology, future versions of should address morphology in a yet broader sense. This could include the acquisition of auxiliaries and modals or the acquisition of the noun phrase (determiner-noun) in Modern Greek. More plausible models of morphological development should also abandon the monosyllabic artificial language approach of the MIG. Such models will need to show the learnability of training sets consisting of realistic multisyllabic inflectional examples, as well as the role of constraints of the early linguistic environment of the child – derived from child-directed corpora – in empirical effects of morphological development (e.g., U-shaped learning curve for the learning of irregulars). Future versions of the MIG should also consider semantic distinctions between different words, possibly incorporated in psycholinguistically plausible distributed representations of lexical semantics. Such models could also include different phases of learning and differences in morphological production in different ‘modes’, e.g., inflection from stem or from meaning (Woollams et al., 2009), that is, be more general across ‘task’.

More broadly, although the focus of the MIG was on development and the extent to which changes in the learning profile of the model were similar to the profiles of children acquiring English or Modern Greek as a first language, there were several ways in which the view of morphological development in the model was static and referring to adult linguistic knowledge. For example, the model assumed a static structure of the linguistic environment (non-incremental training), a fixed amount of neurocomputational resources available to the learning system (cf. Ruh & Westermann, 2009), and that the different types of linguistic knowledge (phonology, lexical semantics, grammatical class and target inflections) are fully matured at the onset of morphological development. A fuller mechanistic account of language development will need to include developmental accounts for all these features.

Finally, it is important for a computational account of morphological development to be able to simulate deficits presented in atypical language development (e.g., SLI; Leonard, 1998). Our current work involves extending the MIG, in which we use the model to evaluate the ability of different etiological considerations of the impairment to capture the morphological profile of SLI in English and Modern Greek.

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Figure captions

Fig. 1.The architecture of the MIG. The light grey frames analyze the structure of the input and the output representations of the network in the English version of the model; in particular, when the network is asked to produce the plural of the noun 'cat'. The dark grey frames explain the structure of the input and output representations in the Greek version; in particular, when the network is asked to produce the 2nd person singular of the perfective past tense for the stem 'pEft-' (corresponding to the Modern Greek verb for the meaning 'to fall'). The two main cross-linguistic differences in the application of the architecture to the two languages concern: (1) the inclusion of an increased number of phonemes, as well as stress, in the phonological representations of the Modern Greek version; and (2) the structure of the Target Inflection representations, which include inflections/grammatical categories appropriate to the two languages.

Fig. 2. Graphical depiction ('wordle' graphs) of relative frequencies of different items in the English training set. Frequencies were based on a tagged corpus and larger fonts indicate higher type frequencies. The top graph (enclosed in the rounded rectangle drawn with a solid line) depicts type frequencies in the whole training set. The middle and bottom graphs (enclosed in rounded rectangles drawn with a dashed and a dotted line) refine type frequencies in the past tense of verbs and the plural of nouns (respectively), distinguishing allomorphs and clusters of irregulars. The middle and the bottom graphs are mapped onto the corresponding elements of the top graph.

<u>Fig. 3</u>. Graphical depiction ('wordle' graphs) of relative frequencies of different items in the Modern Greek training set. Frequencies were based on sampling of the HNC corpus (Hatzigeorgiu et al., 2000) and descriptions in Stephany (1997) and Stavrakaki and Clahsen (2009). Larger fonts are used to indicate higher type frequencies. The top graph (enclosed in the rounded rectangle drawn with a solid line) depicts type frequencies in the whole training set. The bottom graph (rounded rectangle drawn with a dashed line) focused on the perfective past tense, including conjugational classes and different person/number combinations. The bottom graph is mapped onto the corresponding elements of the top graph. There is a many-to-one correspondence (unlike Fig. 1) indicative of the fusional character of Modern Greek Inflectional Morphology.

<u>Fig. 4</u>. Overall accuracy of the MIG in the English and the Modern Greek training set. The thick lines (continuous: English; dotted: Modern Greek) are the average performance of the model over 10 replications. The thin colored lines depict performance in 10 replications. In each epoch of training the network was exposed to 1,600 input-output mappings.

<u>Fig. 5</u>. Accuracy rates for different inflections in the English version of the MIG for the first 200 epochs of training. The black horizontal line at 90% corresponds to the criterion for the order of emergence of inflections considered in Brown (1973).

<u>Fig. 6</u>. Acquisition of the regular past tense in human data and the English version of the MIG. (a) Learning profile of the regular past tense in van der Lely and Ullman (2001); (b) Learning profile of the regular past tense in MIG; (c) Model output versus human data on regular past tense. The comparison of the model with the human data is based on three stages of training in which the model and the human data were matched on correct performance on regular verbs.

Fig. 7. Acquisition of the irregular past tense in human data and the English version of the MIG. (a) Learning profile of the irregular past tense in van der Lely and Ullman (2001); (b) Learning profile of the irregular past tense in MIG; (c) Model output versus human data on irregular past tense. The model and the human data are matched on correct performance on regular verbs (see also Fig. 6).

Fig. 8. Error patterns in the genitive case of the singular number for different conjugational categories (neut 1A, neut 1B, neut 2, and neut 3) of neuter nouns. Continuous lines indicate overgeneralizations of nominative/accusative (‘default’) forms, while dashed lines indicate overgeneralizations of genitive suffixes from other conjugational classes.

Fig. 9. Acquisition of the first and second person singular of the present tense of verbs in conjugational class 1a. Error patterns suggest that the MIG captures the production of i-forms, i.e., an analogue of ‘default’ inflection in the grammatical class of verbs.

Fig. 10. Order of emergence of grammatical categories in the Modern Greek version of the MIG. (a) Accuracy rates in masculine, feminine, and neuter nouns; (b) Accuracy rates in the nominative plural and the genitive singular of nouns; (c)

Rates of correct responses in the genitive singular case for different conjugational categories of neuter nouns.

Fig. 11. The learning profile of sigmatic perfective past tense in the MIG compared with data from Stavrakaki and Clahsen (2009). (a) Data from Stavrakaki and Clahsen (2009) on sigmatic verbs; (b) The learning profile of the 2nd person singular of the conjugational class 1; (c) Human data versus modeling results, for sigmatic verbs. Comparisons were based on matching the model and the human data on performance on sigmatic verbs.

Fig. 12. The learning profile of the non-sigmatic perfective past tense in the MIG compared with data from Stavrakaki and Clahsen (2009). (a) Data from Stavrakaki and Clahsen (2009); (b) The learning profile of the 2nd person singular of the conjugational class 2a; (c) Human data versus modeling results, for non-sigmatic verbs. The model and the human data were matched on performance on sigmatic verbs, cf. Fig. 11.

Fig. 13. Mean amplitude of weights from the input to the hidden layer across the training time for the English version of the MIG. (a) Weights corresponding to parts of the network encoding the four basic types of information presented at the input layer, i.e., phonology, lexical semantics, grammatical class, and target inflection; (b) Weights from the units that encode different inflections; (c) Weights corresponding to the semantics of regular and irregular nouns, verbs, and adjectives, and weights from the units encoding the three grammatical classes.

<u>Fig. 14</u>. Mean amplitude of weights from the input to the hidden layer across the training time for the Modern Greek version of the MIG. (a) Weights corresponding to parts of the network encoding the four basic types of information presented at the input layer, i.e., phonology, lexical semantics, grammatical class, and target inflection. Unlike, the English version, phonology in the Modern Greek version of the MIG also includes syllabic stress; the mean weight from units encoding it are depicted separately; (b) Weights from target inflection units encoding different grammatical categories (thicker lines), as well as person-number combinations; (c) Weights from units encoding the semantics of verbs of the four conjugational classes (continues lines), and weights from the units encoding the three grammatical classes.

Table 1. *The system of inflectional morphology in English.*

Word class	Inflection	Morpheme	Allomorphs	Regular example	Irregular example
Noun	Plural	-s	/s/, /z/, /^z/	cat/cats	ox/oxen
Noun	Possessive	-s	/s/, /z/, /^z/	cat/cat´s	n/a
Verb	3rd singular	-s	/s/, /z/, /^z/	eat/eats	n/a
Verb	Past tense	-ed	/t/, /d/, /^d/	look/looked	eat/ate
Verb	Past participle	-ed	/t/, /d/, /^d/	look/looked	eat/eaten
Verb	Progressive	-ing	-	look/looking	n/a
Adjective	Comparative	-er	-	smart/smarter	good/bette r
Adjective	Superlative	-est	-	smart/smartest	good/best

Table 2. *A simplified version of verbal morphology in Modern Greek (bold highlights prefixes and suffixes; underline indicates perfective stems; capital letters in examples denote stressed vowels).*

Conjugational class	Person and number	Present Tense	Imperfective Past Tense	Perfective Past Tense
1	1^{st} singular	trE-ch**o**	**E-**tre-ch**a**	**E**-<u>tre-x</u>**a**
	2^{nd} singular	trE-ch**is**	**E-**tre-ch**es**	**E**-<u>tre-x</u>**es**
	3^{rd} singular	trE-ch**i**	**E**-tre-ch**e**	**E**-<u>tre-x</u>**e**
	1^{st} plural	trE-ch**u-me**	trE-ch**a-me**	<u>trE-x</u>**a-me**
	2^{nd} plural	trE-ch**e-te**	trE-ch**a-te**	<u>trE-x</u>**a-te**
	3^{rd} plural	trE-ch**un**	**E**-tre-ch**an**	**E**-<u>tre-x</u>**an**
2a	1^{st} singular	plE-n**o**	**E**-ple-n**a**	**E**-<u>pli-n</u>**a**
	2^{nd} singular	plE-n**is**	**E**-ple-n**es**	**E**-<u>pli-n</u>**es**
	3^{rd} singular	plE-n**i**	**E**-ple-n**e**	**E**-<u>pli-n</u>**e**
	1^{st} plural	plE-n**ou-me**	plE-n**a-me**	<u>pII-n</u>**a-m e**
	2^{nd} plural	plE-n**e-te**	plE-n**a-te**	<u>pII-n</u>**a-te**
	3^{rd} plural	plE-n**un**	**E**-plen-**an**	**E**-<u>pli-n</u>**an**
2b	1^{st} singular	vlE-p**o**	**E**-vle-p**a**	<u>I-d</u>**a**
	2^{nd} singular	vlE-p**is**	**E**-vle-p**es**	<u>I-d</u>**es**
	3^{rd} singular	vlE-p**i**	**E**-vle-p**e**	<u>I-d</u>**e**
	1^{st} plural	vlE-p**ou-me**	vlE-p**a-me**	<u>I-d</u>**a-me**
	2^{nd} plural	vlE-p**e-te**	vlE-p**a-te**	<u>I-d</u>**a-te**
	3^{rd} plural	vlE-p**un**	**E**-vle-p**an**	<u>I-d</u>**an**

3	1st singular	mi-l**O**	mi-l**OU-sa**	mI-li-s**a**
	2nd singular	mi-l**As**	mi-l**OU-ses**	mI-li-s**es**
	3rd singular	mi-l**A**	mi-l**OU-se**	mI-li-s**e**
	1st plural	mi-l**A-me**	mi-l**OU-sa-me**	mi-lI-s**a-me**
	2nd plural	mi-l**A-te**	mi-l**OU-sa-te**	mi-lI-s**a-te**
	3rd plural	mi-l**An**	mi-l**OU-san**	mI-li-s**an**

Table 3. *Target empirical phenomena in the acquisition of English inflectional morphology.*

Index	Phenomenon	Study providing data for comparison	Quantitative comparison possible?	Model fits data?
ENG 1	Order of emergence of inflections *	Brown (1973); de Villiers and de Villiers (1973)	YES	YES, quantitatively
ENG 2	Error types I and II: overgeneralization and blend errors	van der Lely and Ullman (2001)	YES	YES, quantitatively
ENG 3	Error type III: Omission errors	van der Lely and Ullman (2001)	YES	YES, quantitatively
ENG 4	Frequency-by-regularity interaction	van der Lely and Ullman (2001)	YES	YES, qualitatively
ENG 5	Generalization	Prasada and Pinker (1993); van der Lely and Ullman (2001)	YES	YES, quantitatively

Table 4. *Target empirical phenomena in the acquisition of Modern Greek inflectional morphology.*

Index	Phenomenon	Study providing data for comparison	Quantitative comparison possible?	Model fits data?
GR1	Accusative singular forms serving as base forms of nouns	Stephany (1997); Stephany and Christofidou (2009)	NO	YES, qualitatively
GR2	Number and gender of nouns emerge before case	Christofidou (2003); Stephany (1997); Stephany and Christofidou (2009)	NO	YES, qualitatively
GR3	Late acquisition of the genitive case	Christofidou (2003); Stephany (1997); Stephany and Christofidou (2009)	NO	YES, qualitatively
GR4	Late acquisition of rare conjugational categories	Stephany (1997)	NO	YES, qualitatively
GR5	Accusative neuter forms serving as base form of adjectives	Stephany (1997)	NO	YES, qualitatively
GR6	Number and gender	Stephany (1997)	NO	YES,

	and case of adjectives are acquired similarly to number, gender, and case of nouns			qualitatively
GR7	Late emergence of the comparative	Stephany (1997)	NO	YES, qualitatively
GR8	i-forms serve as base form of verbs/ Subject-Verb agreement	Katis (1984); Stephany (1997); Varlokosta et al. (1996)	NO	YES, qualitatively
GR9	Emergence of aspect and tense	Katis (1984); Stephany (1997)	NO	NO
GR10	Perfective past tense: sigmatic vs. non-sigmatic	Stavrakaki and Clahsen (2009)	YES	YES, quantitatively

Table 5. *Comparison of the rank order of the acquisition of inflections in Brown (1973), de Villiers & de Villiers (1973), and the MIG.*

Inflection	Rank order of type frequencies	Morphological complexity	Rank order in Brown (1973)	Rank order in de Villiers and de Villiers (1973)	Rank order in the MIG
NOUNS: Regular Plural	1	3	2	1	2
VERBS: Regular Past Tense	2	3	5	5	5
VERBS: Progressive	3	1	1	1	1
VERBS: 3rd Singular	4	2	6	5	4
NOUNS: Genitive	5	2	3	4	2
VERBS: Irregular Past Tense	6	4	4	3	6

Key for the third column (Morphological complexity). 1: fully regular, non-allomorphic; 2: fully regular, allomorphic; 3: regular part of quasi-regular domain, allomorphic; 4: irregular regular part of quasi-regular domain).

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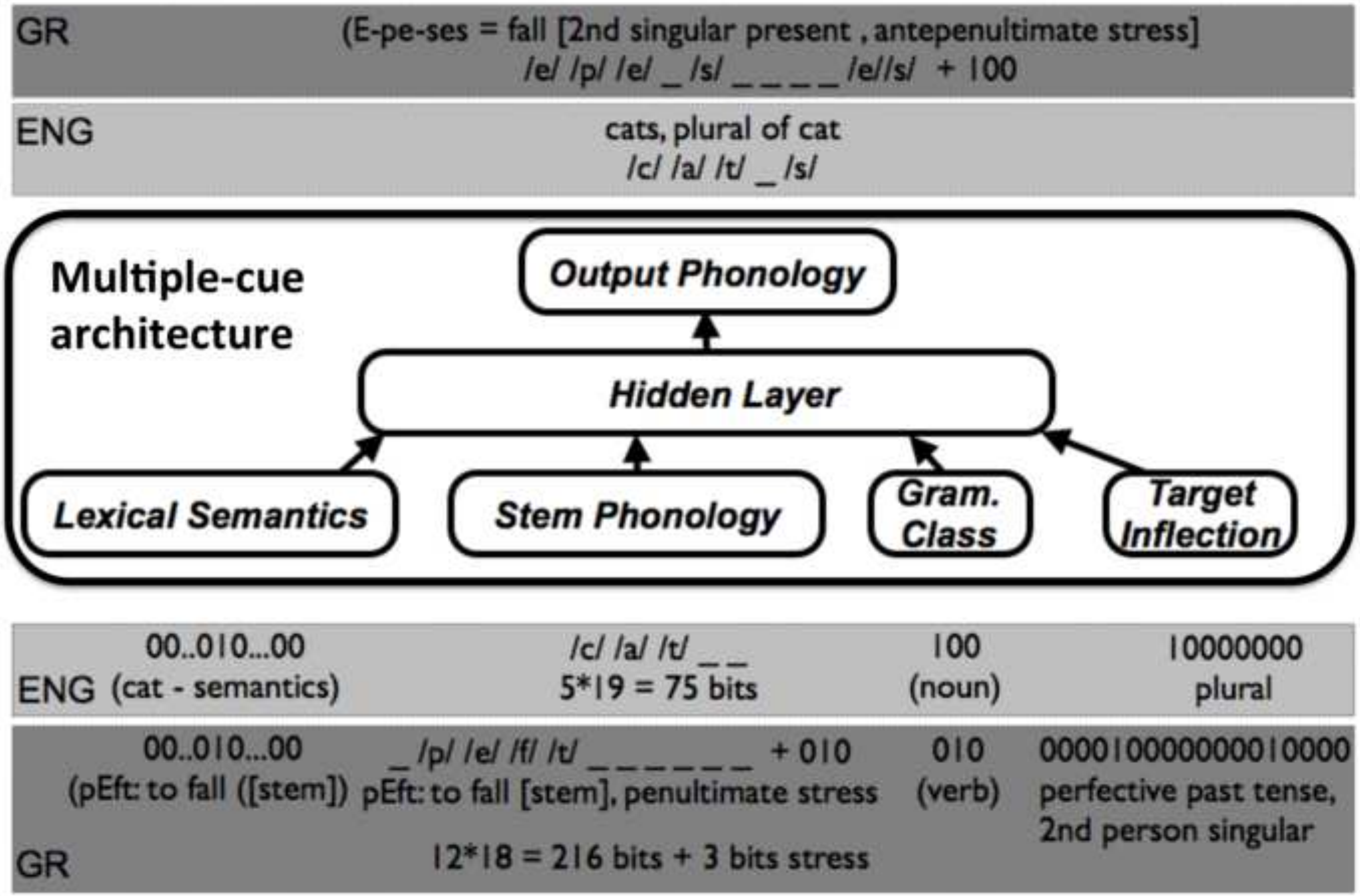
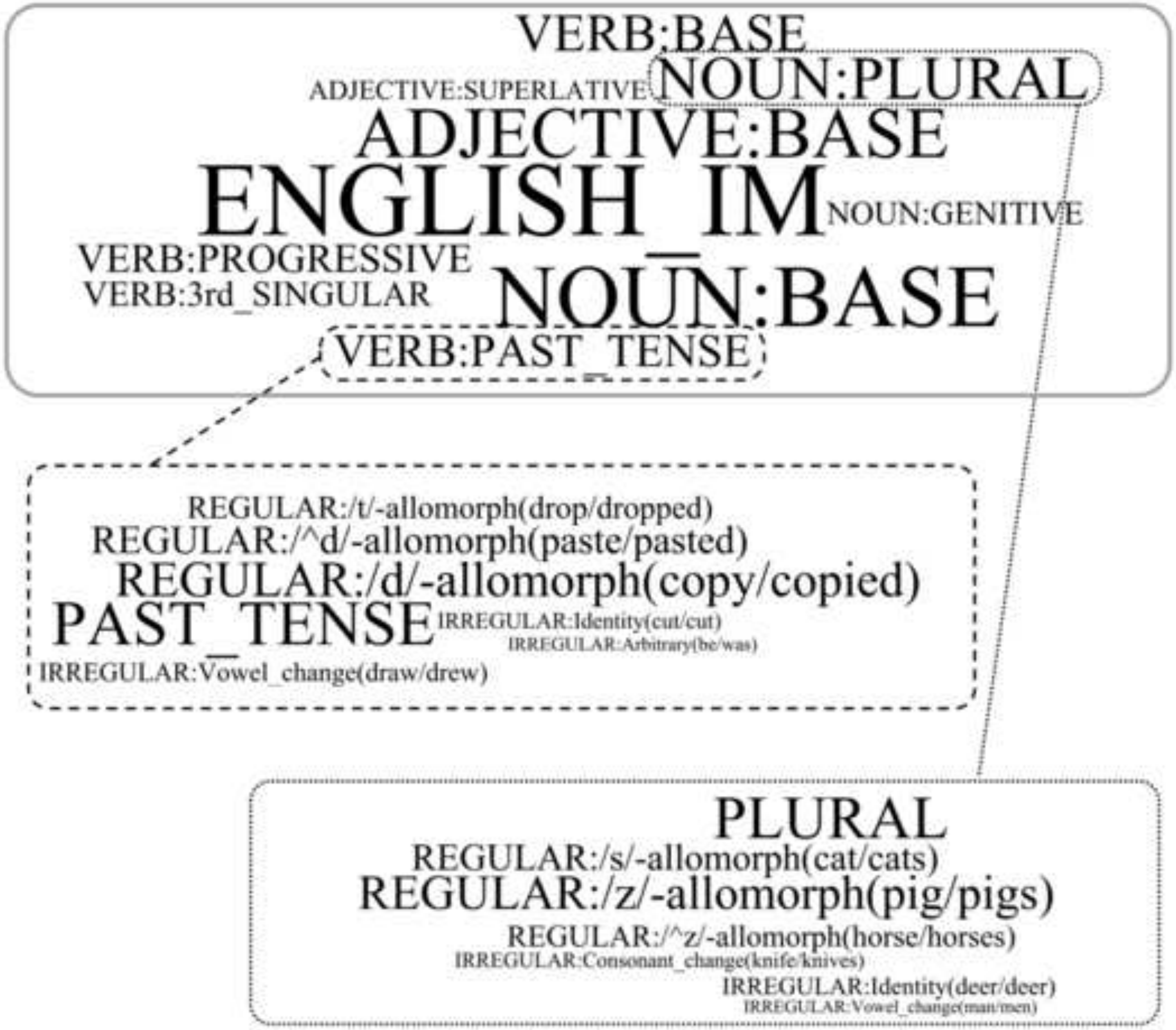


Figure



VERB:BASE
ADJECTIVE:SUPERLATIVE
NOUN:PLURAL
ADJECTIVE:BASE
ENGLISH_IM
NOUN:GENITIVE
VERB:PROGRESSIVE
VERB:3rd_SINGULAR
NOUN:BASE
VERB:PAST_TENSE
REGULAR:/t/-allomorph(drop/dropped)
REGULAR:/^d/-allomorph(paste/pasted)
REGULAR:/d/-allomorph(copy/copied)
PAST_TENSE
IRREGULAR:Identity(cut/cut)
IRREGULAR:Arbitrary(be/was)
IRREGULAR:Vowel_change(draw/drew)
PLURAL
REGULAR:/s/-allomorph(cat/cats)
REGULAR:/z/-allomorph(pig/pigs)
REGULAR:/^z/-allomorph(horse/horses)
IRREGULAR:Consonant_change(knife/knives)
IRREGULAR:Identity(deer/deer)
IRREGULAR:Vowel_change(man/men)

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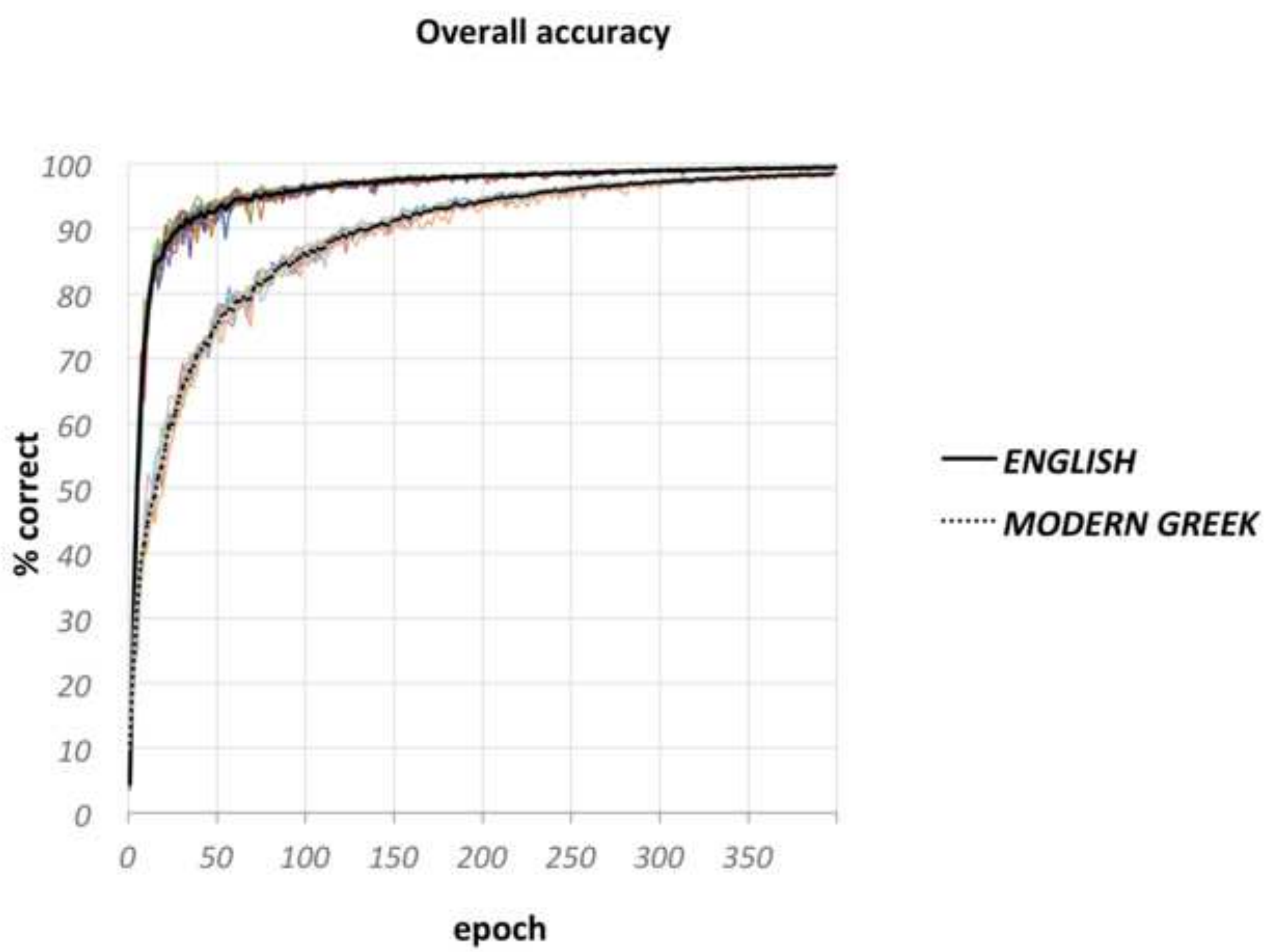
Overall accuracy
% correct
100
90
80
70
60
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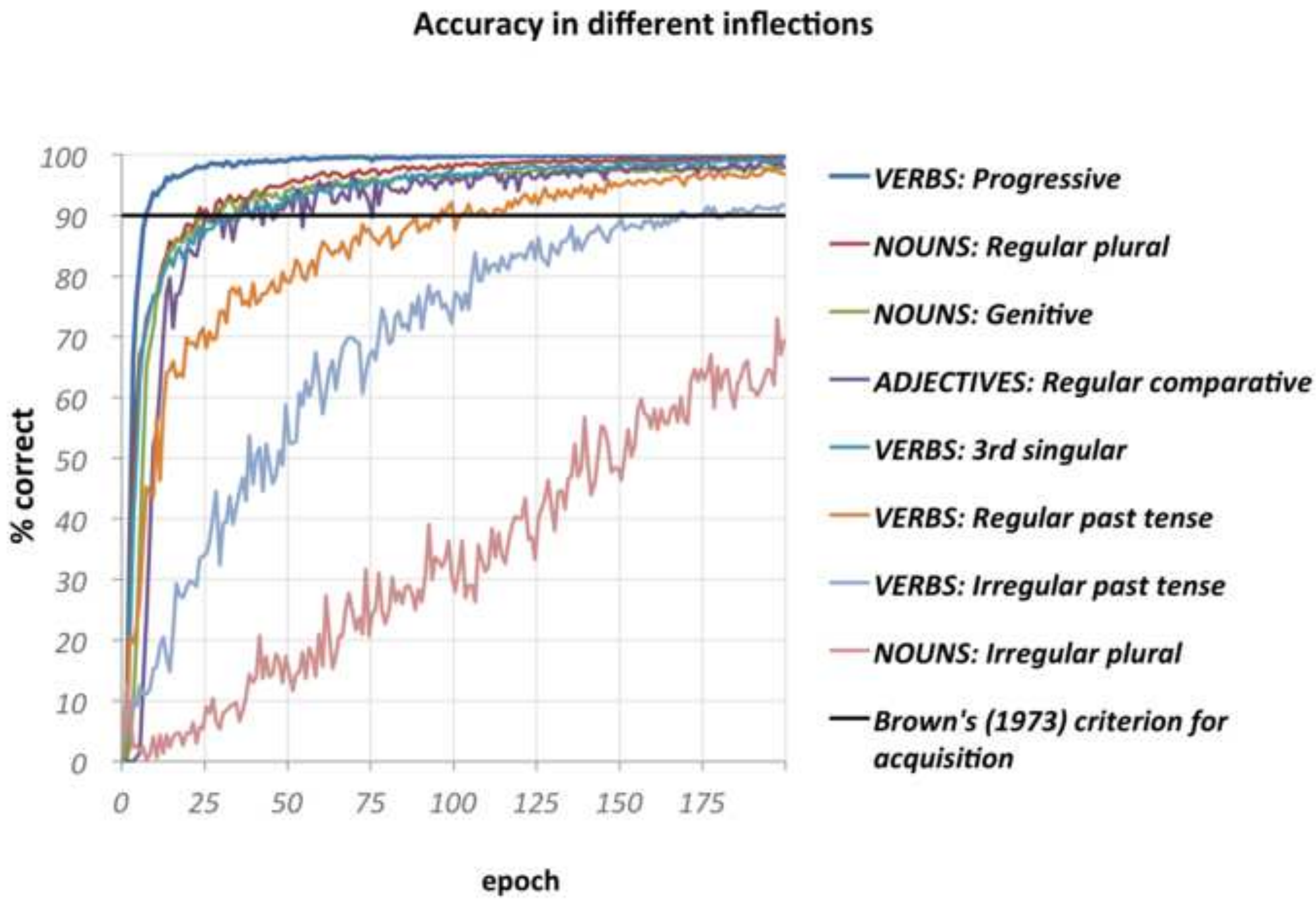
epoch
ENGLISH
MODERN GREEK


Accuracy in different inflections
% correct
100
90
80
70
60
50
40
30
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10
0
0
25
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75
100
125
150
175
epoch
VERBS: Progressive
NOUNS: Regular plural
NOUNS: Genitive
ADJECTIVES: Regular comparative
VERBS: 3rd singular
VERBS: Regular past tense
VERBS: Irregular past tense
NOUNS: Irregular plural
Brown's (1973) criterion for acquisition

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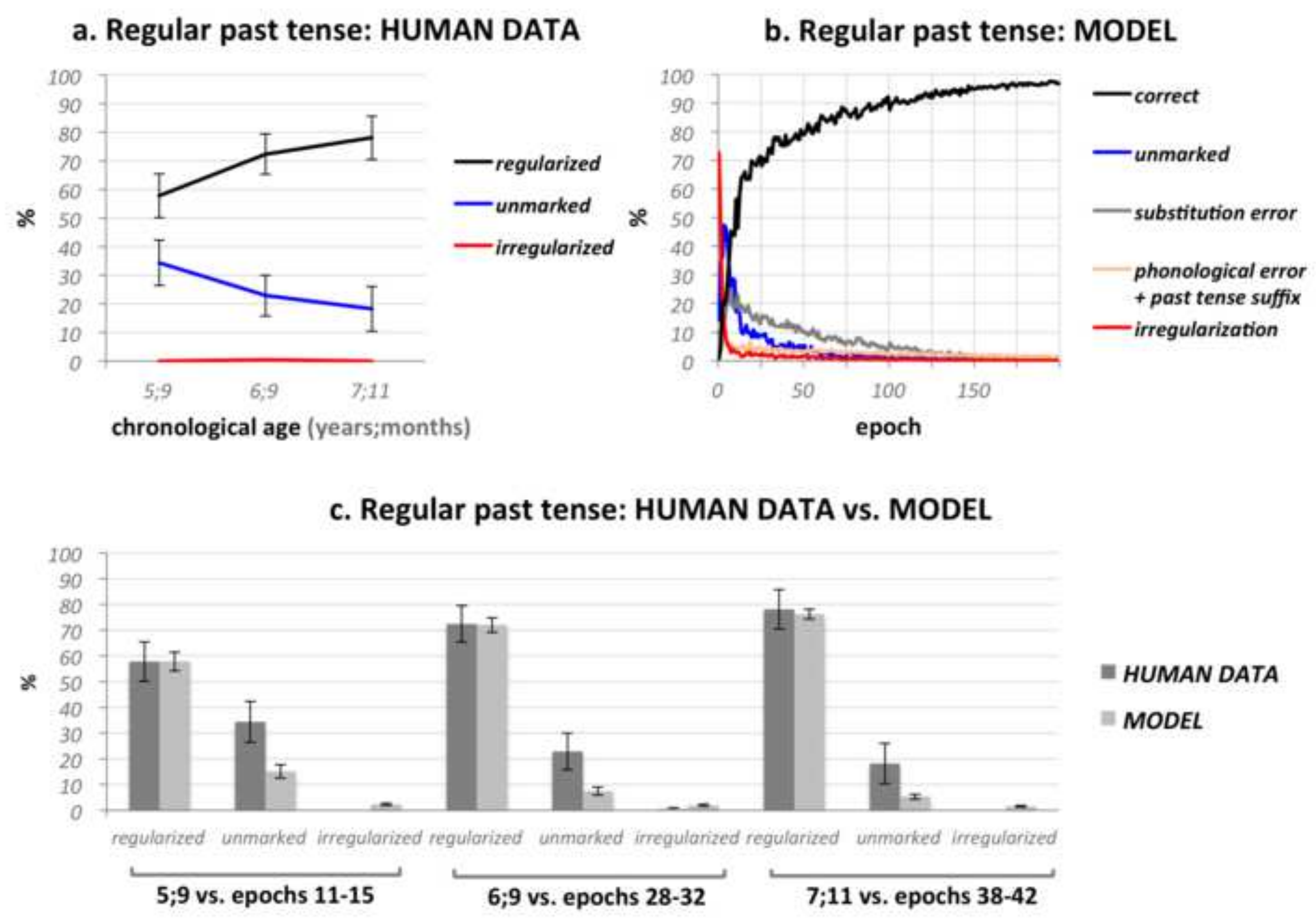

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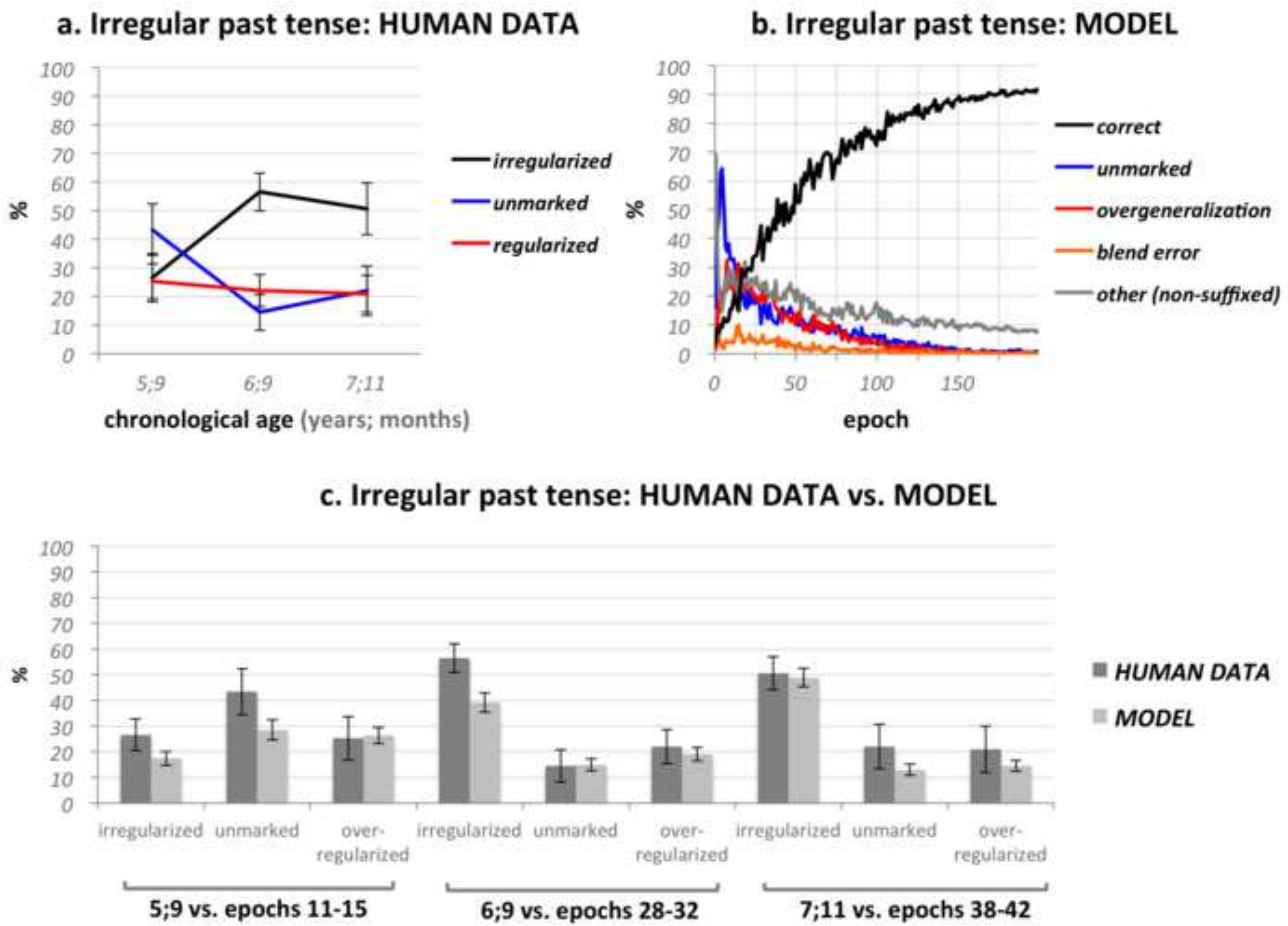

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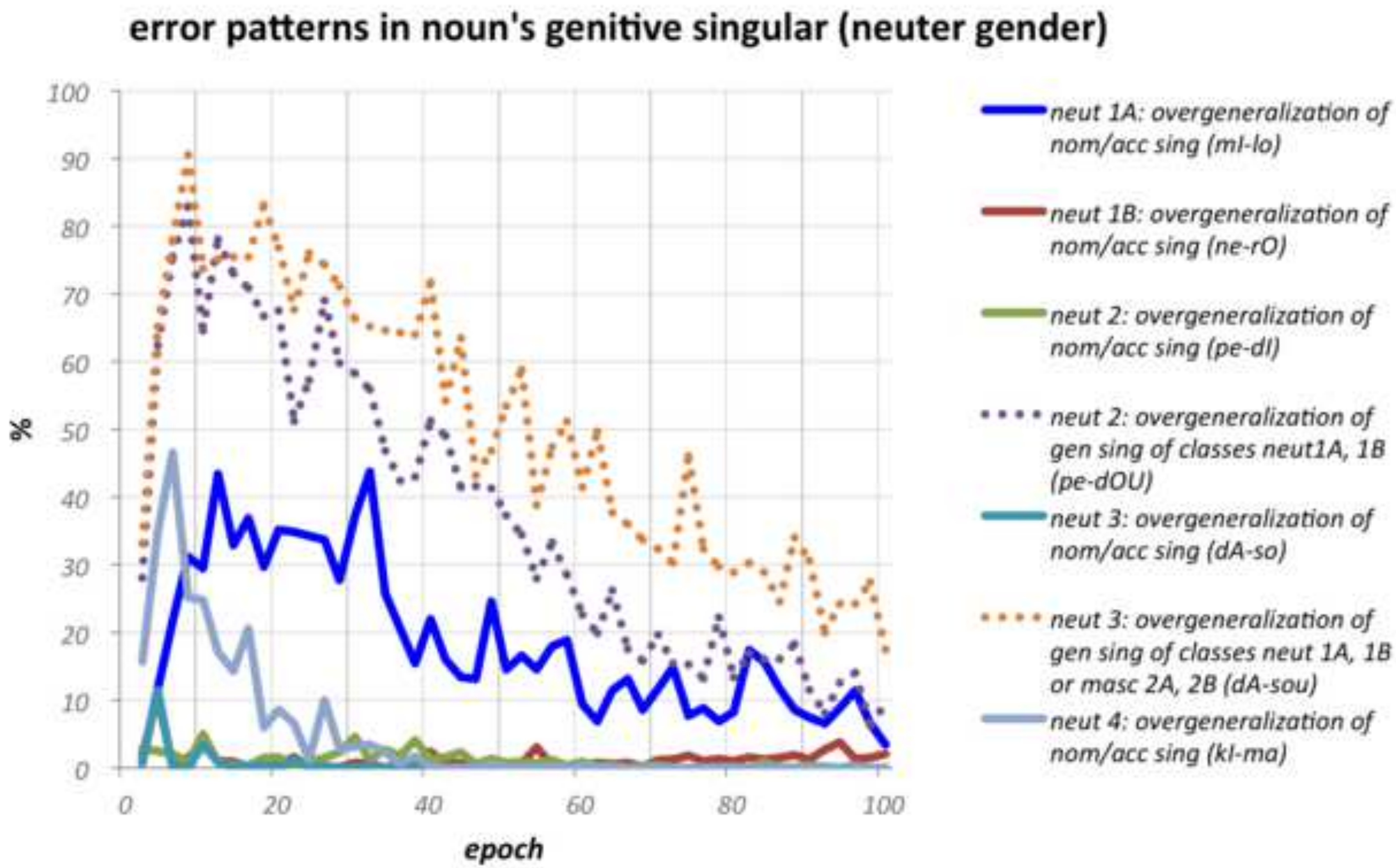

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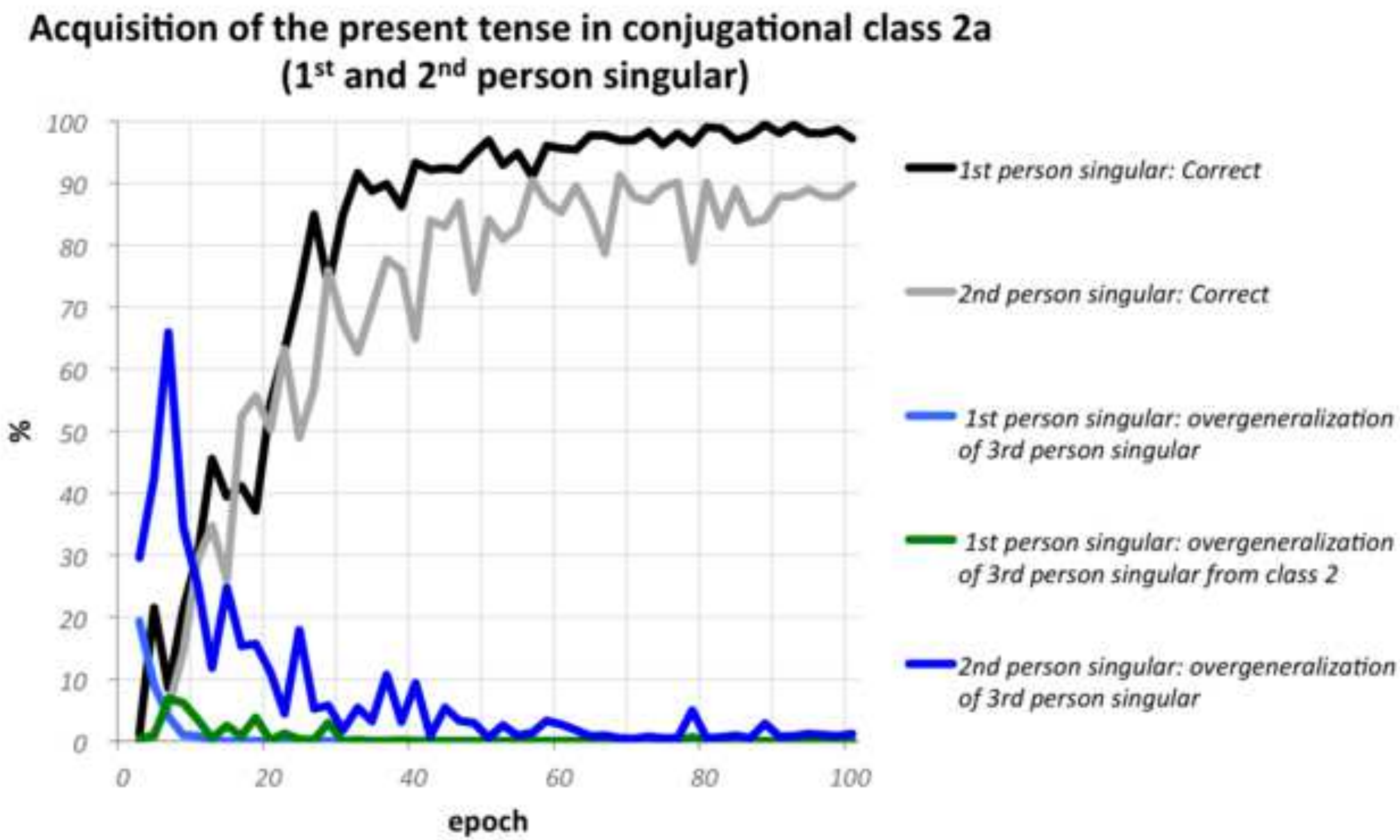

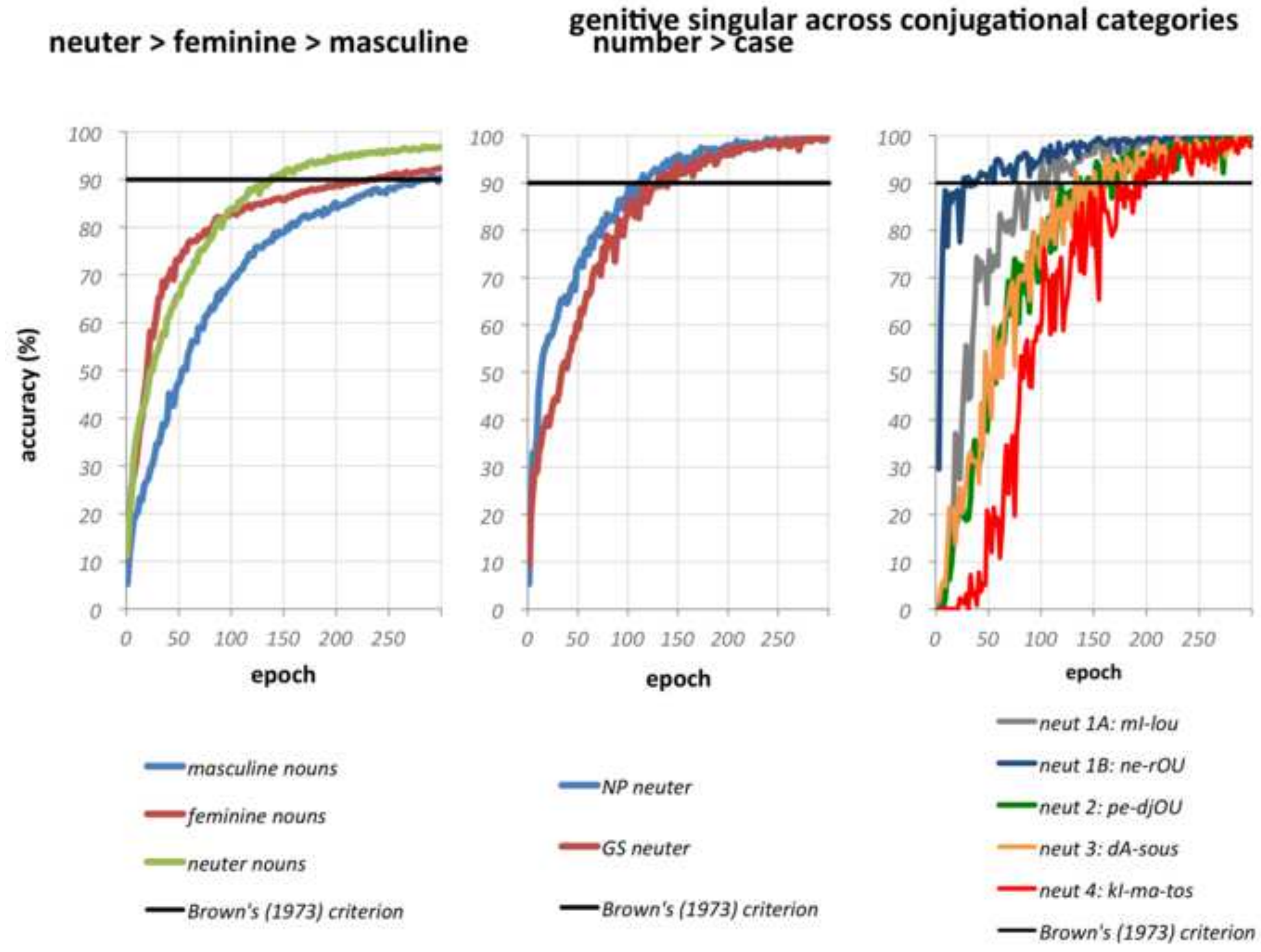
neuter > feminine > masculine
genitive singular across conjugational categories
number > case
accuracy (%)
100
90
80
70
60
50
40
30
20
10
0
0
50
100
150
200
250
epoch
masculine nouns
feminine nouns
neuter nouns
Brown's (1973) criterion
NP neuter
GS neuter
Brown's (1973) criterion
neut 1A: mI-lou
neut 1B: ne-rOU
neut 2: pe-djOU
neut 3: dA-sous
neut 4: kI-ma-tos
Brown's (1973) criterion

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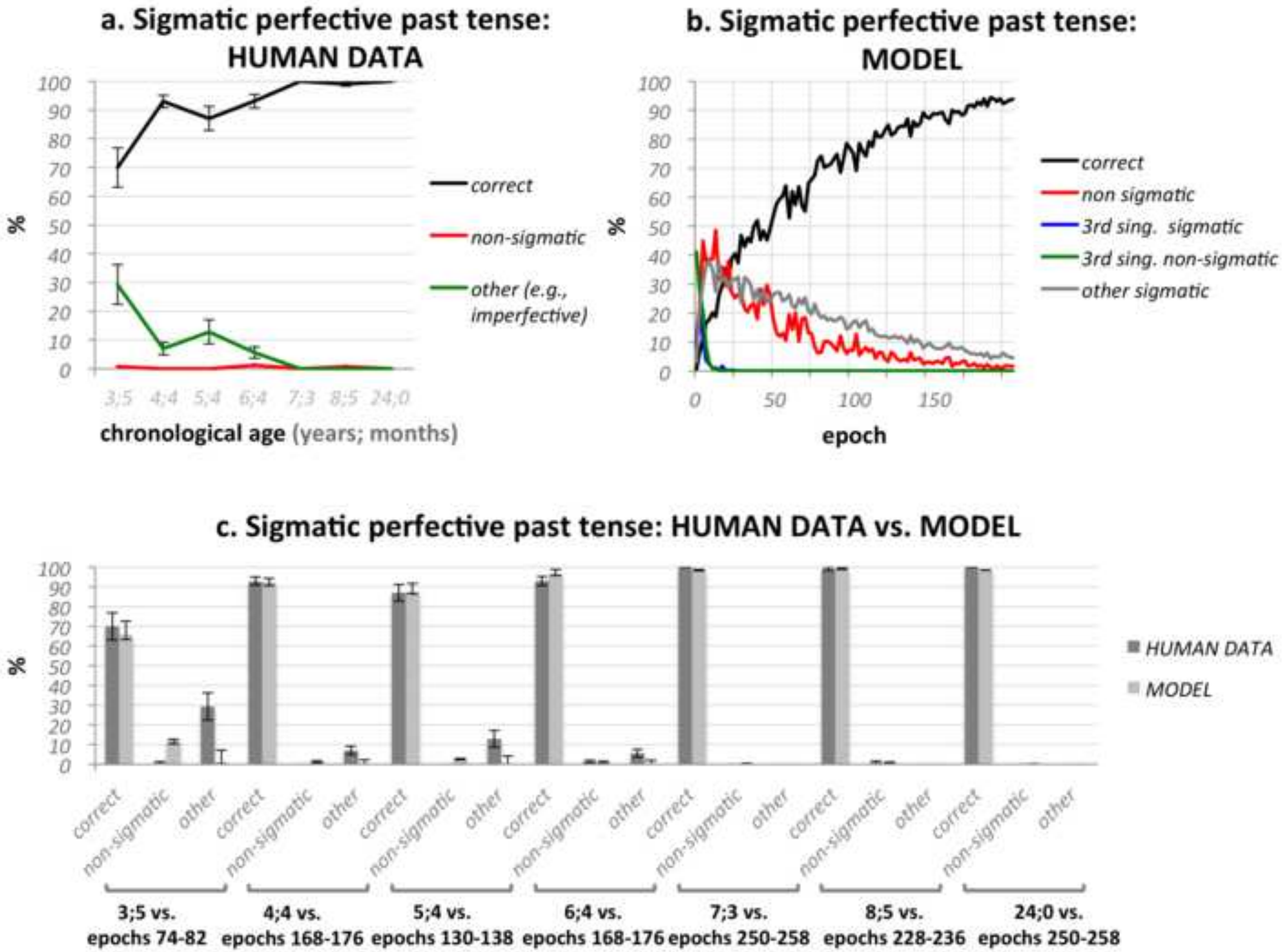

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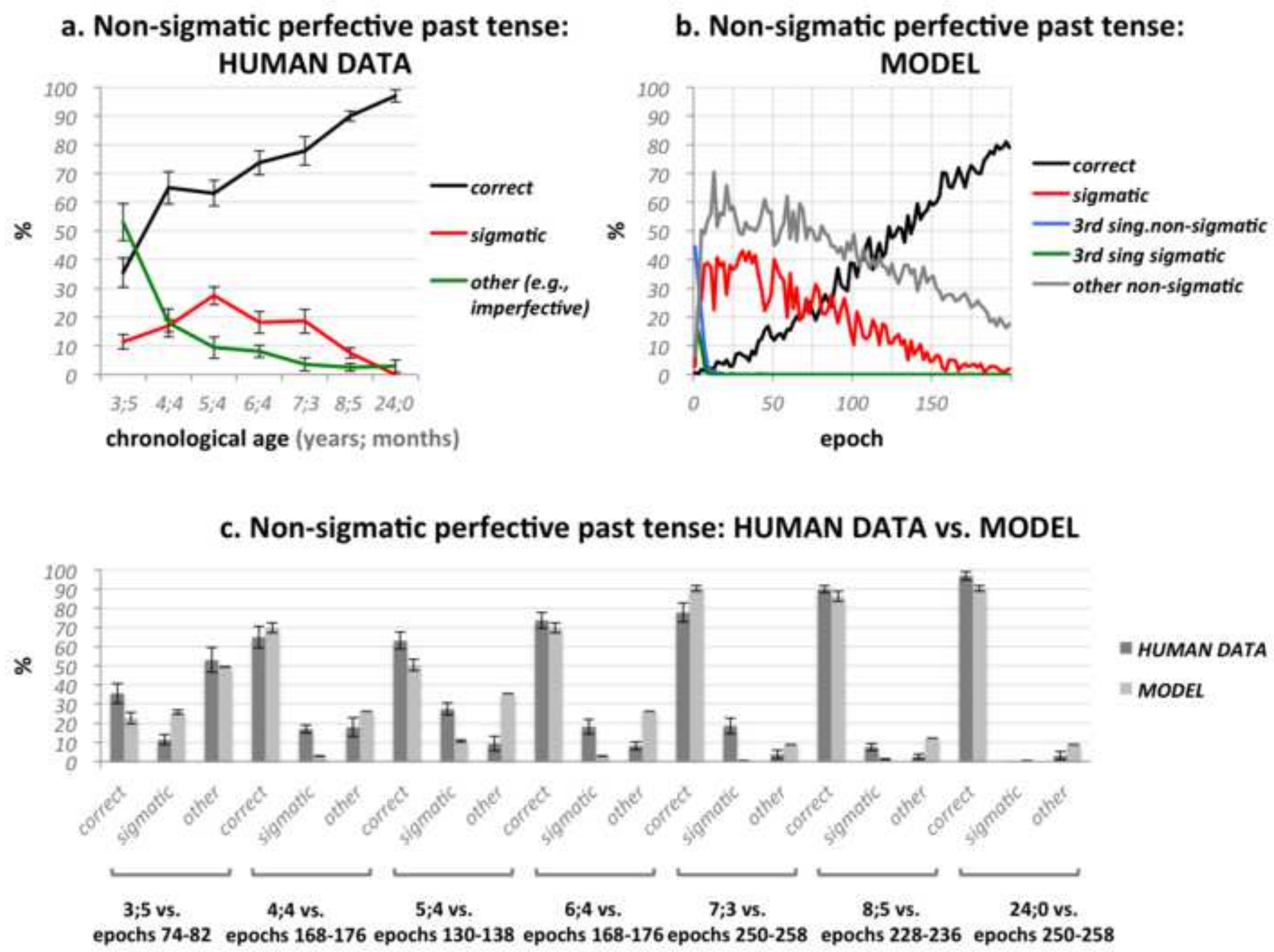

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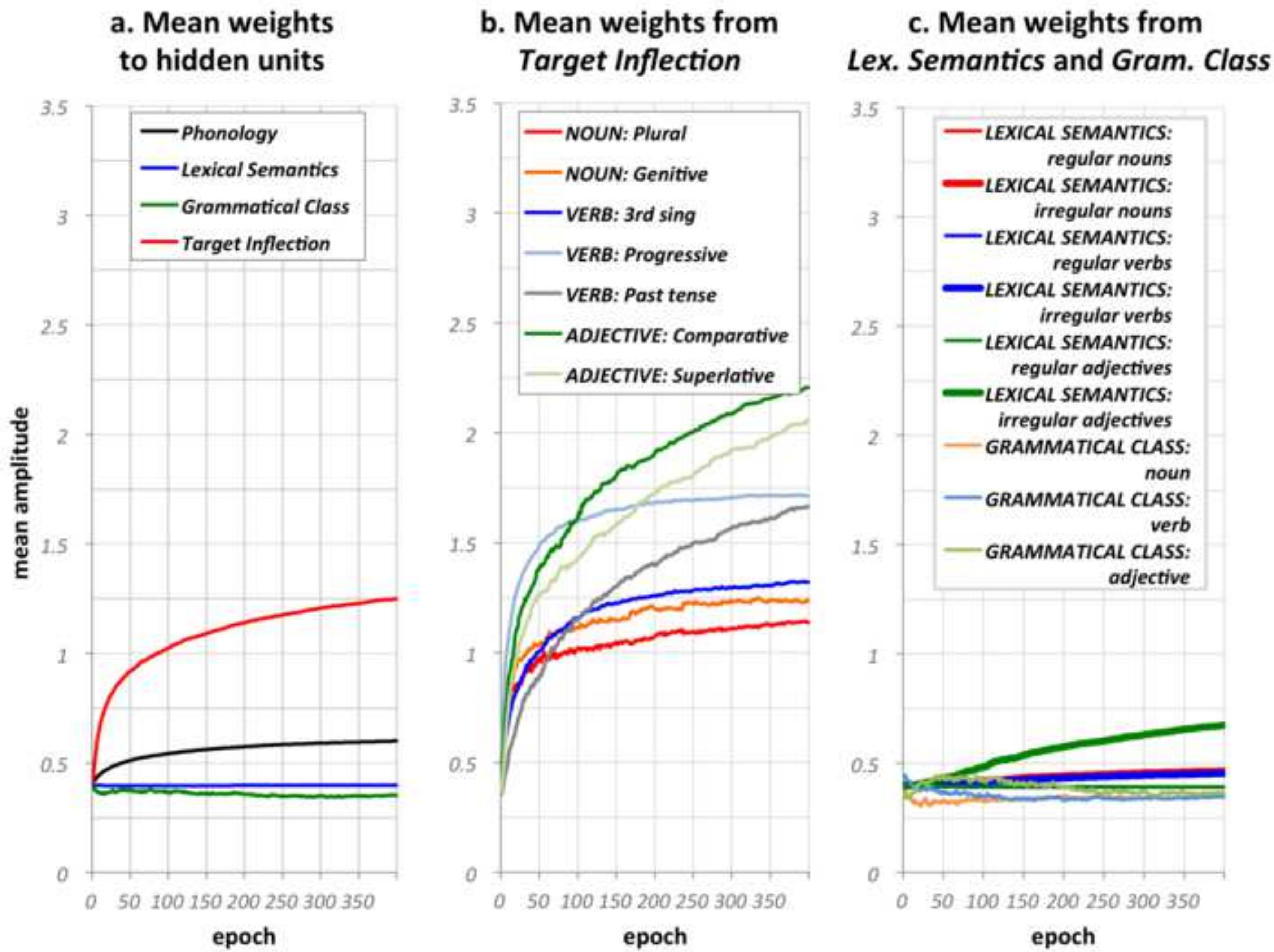

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